Prices, preferences and income effects on consumption of healthy diets in nine African countries

by

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Abstract

Undernutrition is declining in many low- and lower-middle-income countries, yet diet-related noncommunicable diseases are rising, reflecting gaps in diet quality. A key question is whether poverty reduction, a key target for many governments, is sufficient for improving diets. This dissertation examines how diets evolve as incomes rise, assessing the role of prices and preferences in the consumption of healthy diets in nine low and lower-middle-income countries in sub-Saharan Africa. Aim 1 uses data from Malawi to examine how diet quality and consumption patterns vary with income. Aim 2 builds on aim 1, adding demand system estimation for complementary assessment of preferences across 16 food groups and three non-food groups, with data from the eight West African Economic and Monetary Union (WAEMU) countries. Aim 3 returns to Malawi to estimate the costs associated with the preparation of diverse diets, generating lower-bound estimates of the fuel costs required to cook least-cost and reported diets in Malawi. Altogether, these findings describe how food and fuel prices, preferences, and income constraints influence consumers towards and away from healthy diets in a variety of low- and lower-middle income settings.

Keywords: food prices, food demand, healthy diets, dietary transition, West Africa

List of Acronyms

2SLS two-stage least squares
AE adult equivalent
ATAF Automatic Tariff Adjustment Formula
CCT Controlled Cooking Test
CoAHD Cost and Affordability of a Healthy Diet
CoHD Cost of a Healthy Diet
EASI Exact Affine Stone Index
ESCOM Electricity Supply Corporation of Malawi
FBDGs food-based dietary guidelines
F&V fruits and vegetables
GDQS Global Diet Quality Score
HDB Healthy Diet Basket
hGDQS household Global Diet Quality Score
IHPS Integrated Household Panel Survey
IHS5 fifth Integrated Household Survey
IV instrumental variables
KJ kilojoule
LNS legumes nuts and seeds
LPG liquefied petroleum gas
LSMS Living Standards Measurement Survey
MAR Mean Adequacy Ratio
MERA Malawi Energy Regulatory Authority
MFGA Mean Food Group Adequacy
MJ megajoule
MWK Malawi Kwacha
NAR Nutrient Adequacy Ratios
NCD non-communicable disease
NRFI Nutrient-Rich Food Index
NSO National Statistical Office
OLS ordinary least squares
PPP Purchasing Power Parity
WAEMU West African Economic and Monetary Union

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Chapter 1

Introduction

This dissertation addresses the challenge of improving access to healthy diets in low- and middle-income countries, focusing on Malawi and the eight countries of the West African Economic and Monetary Union (WAEMU). In the context of a "global syndemic" of obesity, undernutrition, and climate change, as identified by the Lancet Commission (Swinburn et al., 2019), there is an urgent need to improve shared drivers of these problems, including food systems. Low-income countries in sub-Saharan Africa are highly exposed to climate-related risks, including droughts and floods, and face persistent undernutrition alongside an increasing prevalence of overweight and diet-related non-communicable disease (NCD).

Diet quality improvements are necessary for improved health and well-being, but remain elusive, partly due to the complexities of individual and household food choices. Biological and physiological processes shape preferences, along with cultural influences (Atkin, 2013, 2016; Atkin et al., 2021) and other factors that interact with the effects of price and income (Masters et al., 2022b; Finaret and Masters, 2019). While historical data demonstrates that higher-income individuals tend to consume diets that facilitate greater height growth and longer lifespan, more nutrient-dense or healthful diets are not guaranteed with increased income (Masters et al., 2022b).

Due to availability or affordability constraints, nearly three billion people globally are unable to access merely the least-expensive combination of foods recommended for health (FAO; IFAD; UNICEF; WFP; WHO, 2024b, 2020). Research on the food supply suggests that in Sub-Saharan Africa, only starchy staples are available in recommended amounts, with insufficient quantities of oils and fats, vegetables, fruits, legumes, nuts and seeds, and animal-source foods and legumes, nuts and seeds have experienced significant change in supply towards target amounts in the region (Costlow et al., 2025).

Issues of food availability and cost say nothing of the cost of fuel or water needed to prepare those foods. Addressing market failures to increase availability and reduce retail prices of diverse foods, increasing incomes, and enhancing social protection systems are expected to increase access to healthy diets but are surely insufficient given the multitude of constraints consumers in low-income countries face when making food choices.

For example, meal preparation costs and time use influence food choice in unknown ways. In Malawi and many other countries where biomass fuels are the primary cooking fuel, the opportunity cost of cooking fuels is high. Tanzania's poor consumers pay more for energy sources, which is likely the case in similar settings and adds to concerns about the accessibility of healthy diets among the most vulnerable (Olabisi and Richardson, 2022). However, there is limited empirical evidence on the magnitude of meal preparation costs, due in part to a lack of data on the many facets of meal preparation. Time use data is challenging to collect and analyze, as people often multitask, for example, caring for children and cleaning while preparing and cooking meals. Similarly, there is extensive documentation of fuel and stove-stacking, which refers to the concurrent use of multiple stoves and fuels in cooking and heating.

Interventions to help the most vulnerable must consider the potential of any policy to negatively impact diets or the food system. Many households who can afford healthy diets do not consume them, and as countries get wealthier, a rising prevalence of diet-related disease has been documented. Data collected in 2021 for 41 low-and-middle-income countries documented a trend in simultaneous increases in the consumption of health-protective foods and consumption of unhealthy foods (Global Diet Quality Project). Although income growth and social protection programs are crucial, they are insufficient to address persistent barriers to healthy eating. This dissertation explores how the cost of foods, fuel, and time influence dietary patterns across different settings.

The overarching aim of this dissertation is to examine the factors that influence the cost, affordability, and consumption of healthy diets in some of the world's lowest-income settings. Importantly, this research moves in the same direction diet quality and food security measurement has moved in recent years, by examining functional food groups rather than calories or isolated nutrients, in line with dietary guidance and consumer behavior. Specifically, I use retail prices to explore subnational variation in food and fuel costs associated with consuming recommended diets.

These insights can inform policy debates and programs to bring healthy diets within reach for the most vulnerable and influence the behavior of those who could consume healthy diets but do not. Insights from this research can inform national governments and development partners on how to design interventions that improve diet quality. These include refining food assistance, regulating vendor foods, adjusting trade policy, and investing in cooking fuel technologies and infrastructure to reduce barriers to home meal preparation. Furthermore, this research also seeks to inform governments monitoring the cost and affordability of healthy diets about possible policy analyses and work that can be done to take action once data on Cost and Affordability of a Healthy Diet (CoAHD) are available on a regular basis.

Chapter 2 explores the relationship between household income and diet quality in low-income contexts, with an interest in exploring diet quality as defined by dietary guidelines and food-group-based approaches. We hypothesize an inverted-U relationship between income and diet quality, as greater purchasing power allows for healthier diets among the lowest-income households, but at sufficiently high incomes, food choice is driven by other factors such as taste, convenience, and cultural aspirations. Chapter 3 explores this same relationship between household income and diet quality in low-income contexts with a deeper analysis

of preferences using a full demand system analysis, this time in a more diverse geographic setting of the eight WAEMU countries. Chapter 4 returns to Malawi, where I estimate the cost of cooking food, to understand whether meal preparation costs impede access to and consumption of healthier diets.

Chapter 2

Revealed preferences towards and away from healthy diets

Abstract

Many low and lower middle income countries have achieved declining rates of undernutrition but are experiencing an increasing burden of diet-related diseases. This paper assesses the relationship between income and diet quality, to inform policy to avoid the double and triple burden of malnutrition while pursuing economic growth. Using household survey data from Malawi, one of the world's lowest-income countries, I find that the relationship between income and diet quality is positive but non-linear. I do not find support for the hypothesis that the relationship is non-monotonic. Diet quality is associated with income such that income support and economic growth are expected to improve diets while still leaving many households at high risk of poor diet-related health outcomes. Diet quality levels off at incomes of approximately $3.85 international dollars per person per day (2021 PPP), well above the international poverty line ($2.15) and the average cost of the least-expensive healthy diet available in Malawi ($3.03) (FAO; IFAD; UNICEF; WFP; WHO, 2024b). Even the wealthiest households consume vegetables, legumes, nuts, and seeds below recommended thresholds, and consume more calories from starchy staples and discretionary foods than are needed for health. Targeted income increases among households with higher baseline diet quality appear better suited to producing diet quality increases, alongside approaches that target marginalized households or specific food groups.

JEL-Classification: Q18; D12; I14; O15 Keywords: diet quality, income, development

2.1 Introduction

The evolution of malnutrition poses a significant global public health challenge and requires innovative policies to improve health and well-being (Swinburn et al., 2019). Traditionally, malnutrition has been addressed from two disparate perspectives: focusing either on undernutrition and nutrient deficiencies or on obesity and harmful dietary excesses. With

the nutrition transition, namely the shift in dietary and physical activity patterns, along with other demographic changes, a growing number of people experience multiple forms of malnutrition. We now describe the double and triple burden of malnutrition, whereby undernutrition (stunting and wasting), micronutrient deficiencies, and overnutrition (overweight and obesity) can coexist within an individual, household, or population (Popkin; Drewnowski and Popkin, 1997; Popkin et al., 2020b; Wells et al., 2020; Luo et al., 2020; Prentice, 2023). There is evidence that these trends have been exacerbated by the increased accessibility of foods associated with overconsumption of energy or unhealthy dietary components, some of which simultaneously provide benefits such as convenience, safety, and palatability (Reardon et al., 2021c; Hall et al., 2019).

Improvements in diet quality are a necessary but insufficient condition for better health and well-being and their associated economic benefits. To achieve better diet-related health outcomes, a series of conditions need to be met. Foods needed for health must be physically available, either in nearby markets or through other means such as subsistence production or gifts. Available foods must also be economically accessible. Retail prices must be low enough or incomes available for food high enough such that households can purchase them in sufficient quantities while still meeting their non-food needs (Mahrt et al., 2022; Allen, 2017). Recent work has shown that the availability and affordability of healthy diets constrain households' consumption; an estimated 70 percent of people in low-income countries cannot afford even the least expensive diet that meets dietary needs for an active and healthy life, due in part to rising food prices (FAO; IFAD; UNICEF; WFP; WHO, 2024b).

Households must also have the tools and infrastructure needed to prepare and consume healthy foods safely, including cooking fuel, utensils, and the time for meal preparation. Many households still struggle to access improved cookstoves and clean, affordable cooking fuels, which may affect preferences for more convenient foods, which may contribute to a healthy diet or displace healthy foods. And moreover, households must *choose* the foods needed for health and in the appropriate quantities, due to either preferences for their taste or preferences for health over other attributes. Biological and physiological processes shape preferences, along with cultural influences (Atkin, 2013, 2016; Atkin et al., 2021). While historical data demonstrates that higher-income individuals tend to consume diets that facilitate greater height growth and longer lifespan, more nutrient-dense or healthful diets are not guaranteed with increased income. Many other factors interact with the effects of price and income (Masters et al., 2022b; Finaret and Masters, 2019).

A key starting point is whether households are limited by income to improve diets. Early work on food demand focused on the relationship between income and calorie intake, with the estimation of income elasticities of demand that reveal relatively inelastic demand for calories, consistent with biological mechanisms that exist to maintain energy balance (Subramanian and Deaton, 1996; Banerjee and Duflo, 2011). Studies tend to show that increases in income lead to relatively small changes in calorie intake, as households substitute less expensive calories for more expensive calories from higher-quality or more preferred foods (Jawara and Thiele, 2021; Skoufias et al., 2011). A recent meta-analysis of 40 studies and 99 income-calorie elasticities from observational data estimated a mean pooled income-calorie elasticity of 0.3, even after accounting for various biases that affect published estimates (Ogundari

and Abdulai, 2013). An elasticity of this magnitude suggests households are not prioritizing calorie increases over other income uses. A significantly higher elasticity would be expected if households placed a strong priority on increasing calories. The human body has a variety of biological mechanisms to induce such a prioritization in the event of calorie deprivation (Masters and Finaret). However, recent experimental evidence from poor Kenyan households receiving unconditional cash transfers (UCT) suggests calorie-expenditure elasticities twice as large (Almås et al., 2019), while Bellemare et al. 2024 find elasticities an order of magnitude smaller (0.03) among the poor receiving conditional cash transfers in Mexico, Nicaragua, the Philippines, and Uganda. These divergent estimates demonstrate the importance of context-specific studies.

Alongside uncertainty about the magnitude of income-calorie elasticities, early studies did not consider macronutrients (carbohydrates, protein, and lipids) or micronutrients (vitamins and minerals). Recent meta-analyses and cross-country studies find heterogeneous elasticities of demand by country and nutrient, (Santeramo and Shabnam, 2015; Colen et al., 2018; McCullough et al., 2024). McCullough et al. 2024 examined nutrient elasticities in Malawi, Niger, Ethiopia, Uganda, Tanzania, and Nigeria using recent Living Standards Measurement Survey (LSMS) panel surveys and a flexible, utility-theoretic functional form. With few exceptions, the authors found that wealthier consumers have smaller income-intake elasticities than their poorer counterparts, but notable differences in the income elasticities of demand amongst the poorest. Demand for iron was elastic among the poor in only one of the six countries (Nigeria), while zinc was income-elastic for low-income consumers in all countries except Malawi. In Nepal, Ali et al. 2018 find that vitamins and minerals are more income elastic than macronutrients, with particularly large elasticities for vitamins A, B12, and calcium.

In recent years, the consumer demand literature has evolved along with the nutrition community, moving beyond nutrients toward whole diets and dietary patterns. Income elasticities for food groups defined for health have begun to elucidate how incomes may shift people towards or away from dietary patterns that promote health. The evidence shows highly-context specific elasticities. Calories consumed from fruits and vegetables were found to be considerably less income-elastic in urban areas (0.34) than in rural India in 2011 (0.44) (Jumrani, 2023). Bellemare et al. 2024 show that fruits and vegetable expenditures are highly inelastic (0.064) among poor cash transfer recipients in Mexico, Nicaragua, Philippines, and Uganda. These results are supported by global food demand analysis. Gouel and Guimbard 2019 also find that food group income elasticities vary considerably by national income. As expected, cereals and roots and tubers are normal goods at lower national incomes, and inferior goods at higher incomes (Gouel and Guimbard, 2019). The elasticities for fruits and vegetables suggest that consumption does not increase as much at higher levels of national income, which could indicate a move towards less healthful diets.

This body of research, and its recent extensions to nutrient and food group-expenditure elasticities, suggests that even the answers to some of our most fundamental questions about food demand and income dynamics are context-specific and require many studies, particularly as methods and data quality improve. I build on this literature by studying one of the lowest-income countries in the world, Malawi, where an estimated 70 percent of households

live in extreme poverty (Hasell et al., 2022). I estimate the relationship between income and various measures of diet quality. I focus on three diet quality metrics to reflect the realities of the triple burden of malnutrition, and incorporate a new food group-based diet metric that reflects the consensus understanding of the nutrition community of what constitutes a high-quality diet (Herforth et al., 2019; Satija et al., 2018; Bromage et al., 2021). I test the hypotheses that the relationship between diet quality and income is non-linear and non-monotonic. I hypothesize that diet quality improves as low-income households get wealthier, while the relationship levels off and then becomes negative at sufficiently high incomes, when food choice is driven by other factors such as taste, convenience, and aspirations. I expect that diet composition changes with income in a nonlinear pattern, whereby households consume greater quantities of healthful food groups as income rises from the lower income levels. In contrast, I hypothesize that higher incomes are associated with increased consumption of discretionary foods that displace low-cost healthy items such as vegetables, legumes, nuts and seeds, and whole grains, substituting more-desirable but not necessarily healthy items with refined grains and more oils and fats, and sweet and salty foods than would be needed for a healthy diet.

2.2 Background

Malawi is a low-income, land-locked country in eastern Africa, which has struggled to reduce high rates of poverty and food insecurity. Heavy reliance on subsistence agriculture and climatic shocks are persistent problems, and recent macroeconomic problems suggest that social protection will remain crucial to most Malawian households in the coming years (UNICEF Malawi). Cost-effective interventions and transfers are needed to address poverty and the double burden of malnutrition. A third of women of reproductive age live with anemia, and only a quarter of infants and young children eat a diet that meets minimum standards for diversity (Global Nutrition Report, 2025). Although it has lower rates of diet-related NCD than many neighboring countries, Malawi has not made notable progress toward reducing or stabilizing prevalence rates. Nearly 11% of adult women live with obesity. An estimated 30% of adult women live with raised blood pressure and 7% with diabetes (Global Nutrition Report, 2025).

In Malawi, a recent analysis of income elasticities of demand for a Nutrient-Rich Food Index (NRFI) were positive for consumers across expenditure quartiles, with higher elasticities for the two middle quartiles than for the poorest and wealthiest households (McCullough et al., 2024). Other work examining rural households in the 2010 and 2013 Integrated Household Panel Survey (IHPS) suggests that food consumption and dietary diversity increase alongside income, but with decreasing marginal returns (Benfica, 2023). Further, income diversity was positively associated with dietary diversity, as was having a larger share of cash income from non-agricultural sources; higher income diversification and cash availability can improve access to food groups that most households need to purchase, such as animal-source foods and fruits. Understanding heterogeneous responses is crucial for devising impactful policies, for example, to anticipate how different income groups would respond to taxes or utilize government transfers.

The remainder of the paper is organized as follows. Section 2.3 introduces our data and methods and presents descriptive statistics, followed by the more detailed empirical strategy in section 2.4. Section 4.5 presents our results, and I conclude with a discussion in section 2.6.

2.3 Data and methods

This analysis uses data from the IHPS, implemented by the National Statistical Office (NSO) in collaboration with the World Bank as part of the Living Standards Measurement Survey (LSMS) Integrated Surveys on Agriculture initiative (table 2.1). The IHPS monitors agriculture, poverty, vulnerability, and socioeconomic status of Malawian households over time to inform policy design and research. There have been four rounds of the IHPS, with the most recent round conducted from April 2019 to April 2020 (NSO, 2020a). This analysis draws on an unbalanced panel of 5,503 households from the four survey rounds.

Table 2.1: Household survey data

Survey	Data collection period	EAs	Households	Individuals
IHS3	Mar 2010 - Mar 2011	204	3,104	7,677
IHPS1	Apr 2013 - Oct 2013	204	1,908	10,035
IHPS2*	Apr 2016 - Apr 2017	102	2,508	12,266
IHPS3	Apr 2019 - Nov 2019	102	3,178	14,649

Notes: EA = enumeration area. The sampling frame for all surveys was the 2008 Malawi Census.* Prior to the start of the IHPS 2016, due to increasing numbers of households from the 2013 database to be tracked and budget constraints, 102 out of the 204 baseline EAs were selected, and the IHPS 2016 attempted to track all households, individuals that moved away from dwellings they were enumerated in, in 2013 tied to the selected 102 EAs.

The IHPS uses agriculture, community, and household questionnaires to collect information on sample households on various topics, including all food and non-food consumption and expenditure. Given well-documented issues with income data in low-income contexts highly reliant on subsistence agriculture and informal employment, I use consumption expenditure as a measure of income, and refer to income and expenditure interchangeably throughout the text. Total expenditure includes the value of both non-food and food consumption and expenditure, including the value of food produced by the household or received as a gift or in-kind transfer. Given that no individual-level consumption data was collected, I estimate household-level consumption aggregates following the NSO and the World Bank methodology for poverty assessment (NSO and Bank, 2018). I calculate total expenditure per adult equivalent (AE) per day [1] I adjust all expenditures to real January 2024 Malawi Kwacha (MWK) terms for our main regression specifications and international dollars in 2021 Purchasing Power Parity (PPP).[2]

[1] A detailed description of the data cleaning and calculations for consumption aggregates is included in the appendices (6).

[2] In January 2024, the exchange rate was approximately 1 USD = 1,700 MWK.

2.3.1 Diet quality

I examine the quality of observed diets across three dimensions: diet-related risk factors, food groups, and nutrients. The Global Diet Quality Score (GDQS) elucidates risk factors for poor diet quality. I use a measure of mean food group adequacy based on the proportionality of calories across food groups as recommended in food-based dietary guidelines. Mean Adequacy Ratio (MAR) is a measure of nutrient adequacy that has been validated and widely used as an indicator of individual-level diet quality. All diet quality metrics are calculated using IHPS data on the quantity of food consumed by household members over the seven days prior to the interview. The survey contains quantities consumed, sources, and expenditure and quantity data for 142 food items, most of which are collected across all four survey rounds.[3]

I convert quantities consumed in non-standard units to grams, then estimate the quantity consumed per adult equivalent per day from the seven-day recall. Conversion to grams from non-standard units begins with the conversion factors accompanying the Integrated Household Survey, supplied by the World Bank and the NSO. Other conversion factors are extrapolated from the provided conversion factors, which are region and survey-specific, while volume-to-gram conversions were estimated from an available density database (Charrondiere et al., 2012).

I match each food to its calorie and nutrient content and edible portion in food composition tables (FCTs). I rely on food composition from various FCTs, including the Malawi Food Composition Table, the West African Food Composition Table, and the United States Department of Agriculture's Standard Reference 28 (maf, 2019; Vicent et al., 2020; USDA Agricultural Research Service, 2016a).

I assign energy and nutrient needs to each individual within a household, based on age, sex, physical activity levels and maternity, following Schneider and Herforth (2020a) and Schneider et al. (2023). Energy needs are determined based on reference heights and weights for each age and sex. I use calorie needs to generate a household adult equivalent (AE) measure. Energy-adjusted consumption per AE per day is used to calculate all diet quality metrics, to account for measurement error in reporting of total intakes (National Cancer Institute).

Global Diet Quality Score: I use a modified household Global Diet Quality Score (hGDQS), a food-group-based metric that ranges from 0-49. The GDQS was developed to assess diet quality, incorporating risk factors for nutrient deficiency and chronic disease in low-and middle-income countries (Bromage et al., 2021; Intake, 2021, 2022; Miller et al., 2020). While GDQS was validated for individual-level dietary recall data, recent work has used 7-day household recall data to calculate a modified hGDQS (Ahmed et al., 2022a, 2023).

The GDQS categorizes foods into 25 food groups: 16 healthy, seven unhealthy, and two conditionally unhealthy groups (red meat, high-fat dairy). Quantities consumed (grams) for these groups are assessed into low, medium, and high ranges (plus very high for high-fat

[3]Nine specific cooked foods from vendors are included in the recall, but no composition data is available for meals eaten at restaurants.

dairy). Points are allocated based on grams consumed in a 24-hour period in each GDQS food group: points increase with higher consumption in healthy groups and decrease in unhealthy groups. For red meat and high-fat dairy, points increase up to a limit, then decrease.[4] In Malawi, more than two-thirds of households (69%) are penalized for "very high" consumption of high-fat dairy, while more than a third (37%) are penalized for high levels of red meat consumption. The GDQS, ranging from 0 to 49, aggregates points across all 25 groups. Scores below 15 indicate a high risk of both nutrient inadequacy and NCD risk, and 23 or above indicates a low risk.

Mean food group adequacy: I calculate a measure of diet composition which measures the average deficiency below food group calorie targets described in the HDB, a global dietary standard derived from various countries' food-based dietary guidelines (FBDGs) globally (Herforth et al., 2025, 2022b). The HDB was created as a global standard to be used when calculating and comparing the cost and affordability of healthy diets across countries. A HDB contains 2,330 kilocalories across six food groups (figure I). The calorie target meets the energy needs of an active, healthy adult woman and is similar to the average energy requirement for all sex-age-year groups aged three years and older (Herforth et al., 2025). Substitution between items within energy balance allows for variation in the volume and water weight of locally available items in each food group while maintaining a balanced diet in terms of diversity within and between food groups.

$$MAFG = \frac{1}{6}\sum_{i=1}^{6} \min\left(\frac{s_i}{S_i}, 1\right) \tag{2.1}$$

where s_i is the observed intake for food group i and S_i is the recommended calorie share for food group i. [5] Similar to a mean adequacy ratio for nutrients, the mean adequacy of food groups ranges from zero to one, where 1 signifies a diet with calories exactly aligned with calorie target shares of the HDB. The MFGA aligns with the usual higher-is-healthier approach to diet quality scores. [6]

Mean Adequacy Ratio: I calculate a household-level MAR using the Nutrient Adequacy Ratios (NAR) for 19 nutrients (carbohydrate, protein, fat, vitamin A, vitamin C, vitamin B6, vitamin B12, thiamin, niacin, riboflavin, iron, zinc, calcium, magnesium, phosphorus, copper, selenium, and sodium). NAR values are truncated at 1 to prevent the compensation of a nutrient with an NAR greater than 1 for a nutrient with a lower NAR. MAR is calculated by averaging all NAR values. MAR is reported on a scale from 0 to 1, with 0 indicating that household nutrient requirements were not met for any of the 19 nutrients, and 1 indicating that all nutrient requirements were met or exceeded.

Using these three metrics, I see that diet quality is low regardless of income quintile (table 2.2). Using the modified hGDQS, the lowest-income households in Malawi have an average hGDQS score of 9, rising to 14 for households in the highest income category; these scores

[4] The IHPS consumption modules do not provide sufficient detail on food items to infer the fat content of dairy products. I assume all dairy in Malawi is high-fat dairy.

[5] The min operator ensures that the ratio of the observed share to the recommended share is capped at 1.

[6] Properties of the Mean Food Group Adequacy (MFGA) are illustrated by example diets in appendix table II.

indicate high risk of both nutrient inadequacy and NCDs. Diet quality is significantly different across expenditure quintiles. Both the healthy and unhealthy GDQS sub-scores (GDQS+ and GDQS−) are higher among wealthier households.

Table 2.2: Household characteristics and diet quality, by expenditure quintile

	Quintiles of total expenditure					
	1	2	3	4	5	Test
Head educ. (years complete)	4.2 (3.6)	4.8 (3.7)	5.6 (4.0)	6.2 (4.4)	8.7 (5.6)	<0.001
Head age (years)	45.6 (15.0)	43.8 (15.5)	44.5 (15.8)	44.8 (16.6)	43.9 (15.5)	0.116
Children (0-5)	0.8 (0.8)	0.8 (0.8)	0.7 (0.8)	0.6 (0.7)	0.5 (0.7)	<0.001
Male children (5-15)	1.0 (1.0)	0.8 (0.9)	0.8 (0.9)	0.6 (0.8)	0.5 (0.7)	<0.001
Female children (5-15)	1.1 (1.0)	0.9 (0.9)	0.8 (0.9)	0.6 (0.8)	0.5 (0.8)	<0.001
Male working age (15-64)	1.5 (1.0)	1.3 (0.9)	1.2 (0.9)	1.1 (0.9)	1.0 (0.9)	<0.001
Female working age (15-64)	1.5 (0.8)	1.3 (0.8)	1.3 (0.8)	1.2 (0.8)	1.2 (0.8)	<0.001
Male elderly (65+)	0.1 (0.3)	0.1 (0.3)	0.1 (0.3)	0.1 (0.3)	0.1 (0.3)	0.915
Female elderly (65+)	0.1 (0.3)	0.1 (0.3)	0.1 (0.3)	0.1 (0.3)	0.1 (0.3)	0.628
Dist. to district market (km)	32 (21)	31 (23)	32 (25)	31 (26)	28 (26)	0.168
Total expenditure	0.11 (0.06)	0.20 (0.08)	0.28 (0.11)	0.42 (0.17)	1.82 (3.70)	<0.001
hGDQS	8.99 (4.00)	10.37 (3.88)	11.64 (4.08)	12.66 (4.20)	13.82 (4.29)	<0.001
hGDQS-	1.30 (1.38)	1.68 (1.51)	2.03 (1.60)	2.46 (1.75)	2.99 (1.92)	<0.001
hGDQS+	7.87 (3.67)	8.75 (3.58)	9.63 (3.66)	10.21 (3.78)	10.84 (3.75)	<0.001
MFGA	0.37 (0.12)	0.42 (0.11)	0.45 (0.11)	0.47 (0.10)	0.52 (0.10)	<0.001
MAR	0.85 (0.09)	0.87 (0.08)	0.87 (0.07)	0.88 (0.07)	0.88 (0.07)	<0.001

Note: All expenditure is in per adult equivalent per day (2021 PPP). Household Global Diet Quality Score (hGDQS) [0-49], mean food group adequacy (MFGA) [0-1], and Mean Adequacy Ratio (MAR) [0-1] are based on energy-adjusted intakes. Expenditure quintiles were derived for each panel. Household sampling weights applied. Pooled across four panels.

2.4 Empirical strategy

I assess whether the relationship between household income and diet quality is linear, monotonic, or more complex by progressively relaxing functional form assumptions (Skoufias et al., 2009; Jumrani, 2023; Cattaneo et al., 2024). I begin with parametric models, imposing linearity, move to use increasingly flexible parametric models, and finally move to semiparametric models that allow for flexible nonlinear patterns in income while controlling for other factors parametrically. This layered approach is used to describe and formally test nonlinearities and nonmonotonicity in the income-diet quality relationship.

2.4.1 Parametric models

An ordinary least squares (OLS) regression that estimates diet quality as a function of income, controlling for household characteristics, is defined as follows:

$$y_{ht} = \alpha + \beta e_{ht} + \theta x_{ht} + u_{ht} \tag{2.2}$$

where the outcome y_{ht} is diet quality for household h in month-year t, e_{ht} is the natural log of total expenditure per adult equivalent, and x_{ht} is a vector of time-varying household

controls. I use double-selection Lasso to identify the appropriate covariates, which include the age and educational status of the household head; the number of members in each age-sex category in the household; distance to the nearest district market, nearest population center with greater than 20,000 residents, and nearest road; the number of weather-related shocks a household reportedly experienced in the last 12 months, and binary variables for the receipt of free maize and the receipt of other in-kind food transfers.[7] I incorporate household fixed effects to account for unobserved time-invariant household characteristics:

$$y_{ht} = \alpha + \beta e_{ht} + \theta x_{ht} + \rho_h + \tau_t + u_{ht} \tag{2.3}$$

where ρ_h captures household fixed effects and τ_t captures panel fixed effects. The household fixed effects control for food preferences that are time-invariant with respect to the period of study. Evidence from India suggests that household tastes favor foods that were locally abundant for prior generations and that migrants retain their origin-state food preferences (Atkin, 2013, 2016). The panel fixed effects control for covariate shocks that affect the whole population, such as currency devaluations.

Endogeneity will arise in equations 2.2 and 2.3 if e_{ht} is correlated with the error term, u_{ht}. Endogeneity is a concern if income and unobservable factors, such as the quality of food consumed away from home, are correlated, as these unobservables may also affect observed diet quality. Similarly, with reverse causality and omitted variables, poor diet quality could be caused by other factors that also cause lower consumption expenditure. There is evidence that this occurs in extremely low-income contexts like Malawi; poor nutritional status or energy intake could impede productivity and thus earnings, as seen in India among rickshaw drivers and farmers during Ramadan (Strauss, 1986; Schofield, 2014, 2020).

Measurement error is another critical concern. Diet quality metrics and total expenditure rely on some of the same underlying data, namely the food consumption quantities and expenditures, such that there is correlated measurement errors in the dependent and independent variables. While correlated measurement error could result in an upward bias on the coefficient estimates, classical measurement error from imprecise measurement would bias the coefficient towards zero.

To address measurement error, I implement an instrumental variables (IV) approach (Skoufias et al., 2009). I instrument income with an asset-based wealth index constructed from binary ownership of durable, non-productive assets. The first three principal components from a principal components analysis (PCA) are retained and combined into a weighted index, resulting in the following two-stage least squares (2SLS) IV specification:

$$\begin{aligned} \ln(e_{ht}) &= \pi_0 + \gamma z_{ht} + \pi x_{ht} + \rho_h + \tau_t + u_{ht} \\ y_{ht} &= \alpha + \beta \ln(\hat{e}_{ht}) + \theta x_{ht} + \rho_h + \tau_t + u_{ht} \end{aligned} \tag{2.4}$$

where z_{ht} is the asset index.

[7] I use the Stata ivlasso command.

I then relax the exclusion restriction and estimate the bounds of β following the local-to-zero approach of Conley et al. (2012):

$$y_{ht} = \alpha + \beta \ln(e_{ht}) + \gamma z_{ht} + \theta x_{ht} + \rho_h + \tau_t + u_{ht}. \tag{2.5}$$

where γ represents the direct effect of the instrument z_{ht} on the outcome y_{ht}. The plausibly exogenous approach relaxes the prior that $\gamma = 0$, and improves our understanding of the potential magnitude of the relationship between income and diet quality in the face of an endogenous regressor.

While the parametric IV regressions describe the average relationship between income and diet quality, they may obscure important heterogeneity across the distribution of diet quality. Households at the lower tail of the diet quality distribution may respond differently to changes in income than those who have relatively high diet quality. To capture this heterogeneity, I estimate an IV quantile regression. The structural equation of the quantile regression is described in equation 2.6:

$$Q\{y_{ht} \mid x_{ht}\}(q) = \alpha(q) + \beta(q) \ln(e_{ht}) + \delta(q)x_{ht} + \gamma_h(q) + \tau_t(q) + \epsilon_{ht}(q) \tag{2.6}$$

for quantiles $q = 0.1, 0.2, \ldots, 0.9$.

This approach produces a set of parameters $\beta(q)$, one for each quantile of diet quality, thereby revealing whether the income-diet quality relationship varies at different points in the conditional distribution. Quantile regression has an added benefit in that it is more robust to outliers than mean-based methods.

To characterize how the effect of income on diet quality varies across its distribution, I employ distribution regression. This approach involves creating a series of binary variables, each indicating whether a household's diet quality score (y_{ht}) meets or exceeds a specific threshold. These thresholds, denoted y_k, are defined over a grid of 100 evenly spaced points between the fifth and ninety-fifth percentiles of the observed diet quality distribution. For each threshold y_k, I first define a binary outcome variable $D_{ht}(y_k)$ as:

$$D_{ht}(y_k) = \mathbf{1}\{y_{ht} \geq y_k\} \tag{2.7}$$

where $\mathbf{1}\{\cdot\}$ is the indicator function, equal to 1 if the condition is true and 0 otherwise. I then estimate the following Linear Probability Model for each of the 100 thresholds using fixed effects:

$$D_{ht}(y_k) = \alpha_k + \beta_k e_{ht} + \mathbf{x'_{ht}}\theta_k + \rho_h + \tau_t + u_{ht,k} \tag{2.8}$$

Here, e_{ht} is income, $\mathbf{x'_{ht}}$ is a vector of controls, while ρ_h and τ_t are household and year fixed effects, respectively. By estimating this model for each threshold, I obtain a sequence of coefficients, $\{\beta_k\}_{k=1}^{100}$. Plotting these coefficients against the thresholds y_k traces out how the marginal effect of income on the probability of achieving a certain level of diet quality changes across the distribution.

The quantile and distribution regressions use parametric approaches but may reveal patterns missed by models focusing solely on the conditional mean, in order to detect whether the income-diet quality relationship differs in form across levels of diet quality.

2.4.2 Semi-parametric model

To allow for non-linearities in income while controlling for covariates parametrically, I estimate a partial linear model:

$$y_{ht} = z_{ht}\beta + m(e_{ht}) + \epsilon_{ht} \tag{2.9}$$

where z_{ht} is a vector of controls and $m(e_{ht})$ is a nonparametric function of income. I implement this using the *binsreg* package (Cattaneo et al., 2024; Matias Cattaneo et al., 2024), which partitions the income distribution into bins and estimates within-bin means and optionally fitting low-order polynomials. This partial linear specification flexibly estimates $m(e_{ht})$ while including parametric controls x_{ht} and fixed effects ρ_h and τ_t. The associated *binstest* shape restriction tests are applied to the first derivative of $m(e_{ht})$, assessing whether the relationship is strictly monotonic or exhibits curvature such as an inverse-U. The tests use Kolmogorov-Smirnov supremum statistics, with simulation-based inference on the full sample.

In combination, these parametric and semiparametric approaches provide a comprehensive framework for describing and formally testing whether the relationship between income and diet quality is linear, monotonic, or more complex.

2.5 Results

Figure 2.1 provides preliminary support for the hypothesis that the bivariate relationship between income and diet quality is nonlinear, but does not provide sufficient evidence of a non-monotonic relationship. Diet quality, as measured by hGDQS and MFGA, rises until approximately a real total expenditure of $3.85 PPP per AE. However, the relationship is imprecisely estimated at the tails of the distributions, particularly at the higher end of the income distribution, where there are considerably fewer households. The apparent downturn of hGDQS and MFGA at higher levels of expenditure is driven largely by the 2010 panel (appendix 6).

The flattening of the relationship between income and diet quality as measured by hGDQS is driven by a leveling off of both the healthy and unhealthy sub-scores (figure 2.2). Higher unhealthy sub-scores indicate lower consumption of unhealthy foods, so wealthier households are improving quality by consuming more of the recommended groups and less of the "unhealthy" or conditionally unhealthy food groups. Sugar-sweetened beverages, processed meats, and juices drive the unhealthy sub-scores in the sample.

The hGDQS sub-score findings are supported by data on calorie intakes by food group (figure 2.3). Total calories from starchy staples decline the most dramatically among higher income households, but even the wealthiest households consume more starchy staples than recommended in the Healthy Diet Basket. The primary starchy staples consumed in Malawi are

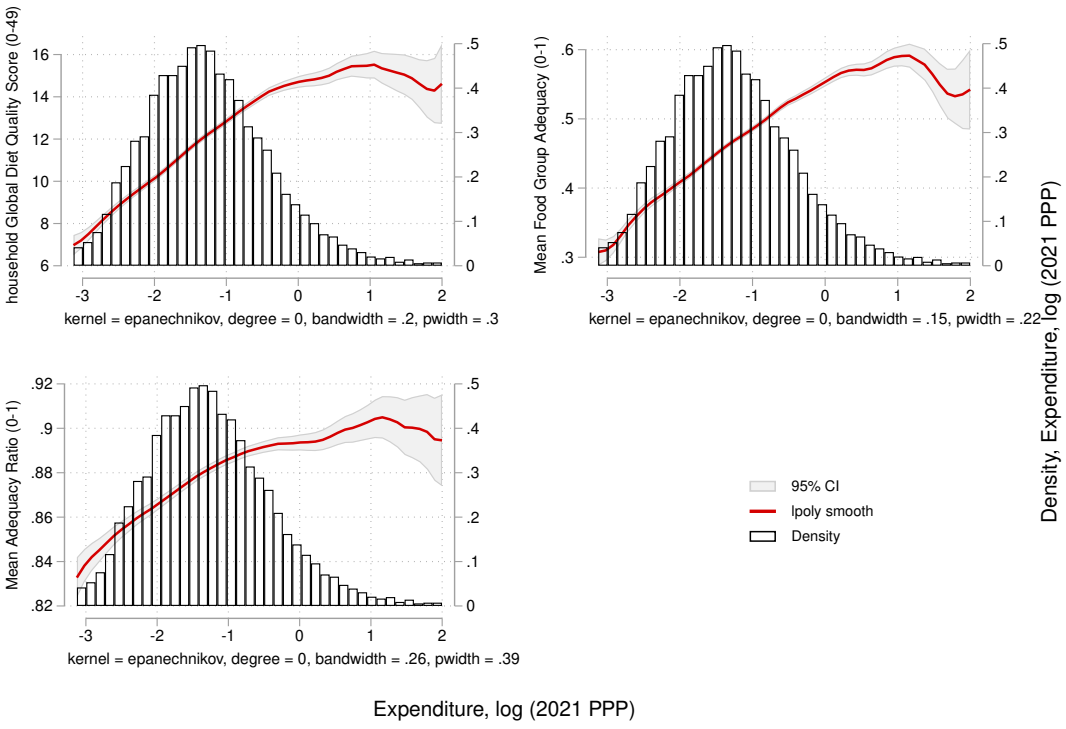


Figure 2.1: Nonparametric bivariate relationship between diet quality metrics and income

Notes: Figures show the smoothed values and 95% confidence bands from kernel-weighted local polynomial regression of diet quality outcomes on logged expenditure. Expenditure is in 2021 PPP/AE/day and is truncated at percentile 1 and 99.

refined grains, including refined maize flour. Both oils and fats and animal-source foods contribute more calories in higher-income households. Declines in fruit, vegetable, and legumes nuts and seeds (LNS) intake among wealthier households also contribute to lower overall diet quality. There is some displacement of calories from healthy food groups with calories from discretionary foods, mainly sugar and sweets, like biscuits and beverages.

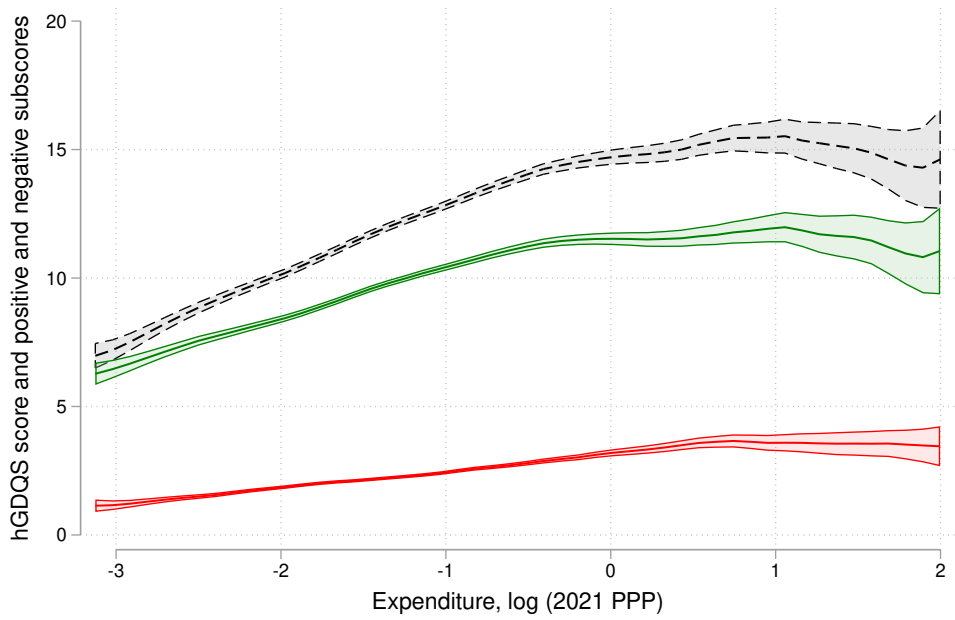


Figure 2.2: Nonparametric bivariate relationship between hGDQS sub-scores and income

Notes: Black dashed line: hGDQS overall score [0-49]; Green solid line: hGDQS positive (+) sub-score [0-32], 16 food groups; Red solid line: hGDQS negative (-) sub-score [0-17], 9 food groups. Figures show the smoothed values and 95% confidence bands from kernel-weighted local polynomial regression of diet quality outcomes on logged expenditure.Expenditure is in 2021 PPP/AE/day and is truncated at percentile 1 and 99.

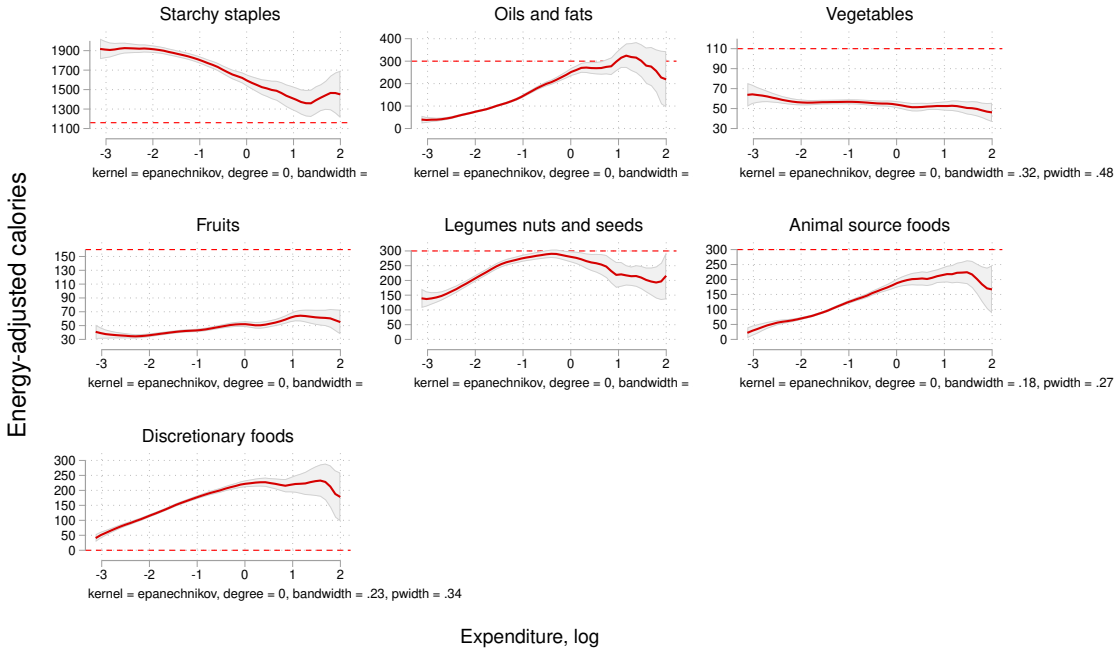


Figure 2.3: Food group consumption relative to HDB targets

Notes: Figures show the smoothed values and 95% confidence bands from kernel-weighted local polynomial regression of calorie consumption per adult equivalent per day in each food group on logged expenditure. Calories are energy-adjusted to meet household needs per adult equivalent. Expenditure is in 2021 PPP/AE/day. Expenditure is truncated at percentile 1 and 99 of total expenditure. Dashed red lines represent corresponding calorie recommendations in the HDB.

Parametric regressions of the relationship between income and diet quality show a positive and statistically significant relationship between income and hGDQS and MFGA. However, these effects are economically insignificant; a doubling of income is associated with a 2.95-point increase in hGDQS from a mean of 11.5 (column 3, table 2.3). When using the GDQS indicator calculated using individual intakes, a GDQS score $\leq$ 15 indicates a high risk of nutrient inadequacy and NCD-related outcomes. Extrapolating this interpretation to the hGDQS, a doubling of income would still leave many households at high risk of negative diet-related health outcomes. Similarly, a doubling of income is associated with a 0.087 increase in MFGA or 0.02 increase in MAR. [8]

Instrumenting income with an asset-based wealth index increases the coefficient on hGDQS from 1.82 in the ordinary least squares (OLS) specification to 2.95 in the comparable IV specification, without household fixed effects and with covariates. The IV helps to purge measurement error in this setting, such that OLS understates the relationship between income on diet quality.

Table 2.3: Conditional relationship between diet quality and income

	hGDQS			MFGA			MAR		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Expenditure, log	3.262***	3.292***	2.947***	0.103***	0.107***	0.087***	0.029***	0.030***	0.020***
	(0.209)	(0.166)	(0.245)	(0.005)	(0.004)	(0.006)	(0.004)	(0.003)	(0.004)
Mean	11.32	11.48	11.49	0.44	0.45	0.45	0.87	0.87	0.87
Survey weights	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Household	No	No	Household	No	No	Household	No	No
Time FE	Panel	Panel	Panel	Panel	Panel	Panel	Panel	Panel	Panel
Controls	No	No	Lasso	No	No	Lasso	No	No	Lasso
N	6114	9294	9058	6091	9270	9034	6091	9270	9034
KP Wald F-stat	656.69	1281.96	584.14	655.80	1264.66	575.87	655.80	1264.66	575.87

Note: hGDQS = household Global Diet Quality Score, MFGA = Mean food group adequacy, MAR = Mean Adequacy Ratio. Values are the coefficients on expenditure from the reduced form of the key 2SLS specifications.

The preferred specification does not include household fixed effects (columns 3, 6, and 9 of table 2.3). This decision rests on the fact that 20 percent of households are only observed once across the four panels. These are dropped when household fixed effects are used, as they do not contribute to the estimation of within-unit variation. Yet, the singleton households have statistically significantly higher expenditure and diet quality as measured by all three metrics (hGDQS, MFGA, MAR), have younger and more educated household heads, fewer children and men of working age, and live closer to large population center and key infrastructure than their counterparts (table 2.4). Expenditure per adult equivalent is also statistically significantly higher among singleton households and the rest of the sample.

[8] Complete regression results are available in Appendix 6.

Table 2.4: Singleton households balance test

	Household only included in 1 round			
	0	1	Total	Test
N	9,775,879 (79.1%)	2,579,842 (20.9%)	12,355,721 (100.0%)	
Head age (years)	45.29 (15.7)	41.56 (15.4)	44.51 (15.7)	<0.001
Head educ. (years complete)	5.76 (4.5)	6.47 (4.6)	5.91 (4.6)	<0.001
Rural (0/1)	0.83 (0.4)	0.81 (0.4)	0.83 (0.4)	0.446
North	0.12 (0.3)	0.12 (0.3)	0.12 (0.3)	0.817
Centre	0.40 (0.5)	0.37 (0.5)	0.40 (0.5)	0.089
South	0.48 (0.5)	0.51 (0.5)	0.48 (0.5)	0.143
Children (0-5)	0.68 (0.8)	0.62 (0.7)	0.67 (0.8)	0.010
Male children (5-15)	0.76 (0.9)	0.64 (0.8)	0.73 (0.9)	<0.001
Female children (5-15)	0.79 (0.9)	0.69 (0.9)	0.77 (0.9)	0.011
Male working age (15-64)	1.26 (0.9)	1.12 (0.9)	1.23 (0.9)	<0.001
Female working age (15-64)	1.30 (0.8)	1.31 (0.8)	1.31 (0.8)	0.709
Dist. (km) to nearest population center (20k+)	29.55 (19.0)	24.49 (17.0)	28.50 (18.7)	<0.001
Dist. (km) to nearest ADMARC depot	7.33 (5.4)	7.23 (5.2)	7.31 (5.3)	0.688
Dist. (km) to nearest district market	32.75 (25.3)	24.00 (18.6)	30.93 (24.3)	<0.001
Weather-related shocks experienced in last 12 months	0.89 (0.9)	1.14 (1.1)	0.94 (1.0)	<0.001
Received free maize (0/1)	0.08 (0.3)	0.12 (0.3)	0.09 (0.3)	0.003
Received free food other than maize (0/1)	0.02 (0.1)	0.03 (0.2)	0.02 (0.1)	0.066
Total expenditure	0.54 (1.9)	0.51 (1.1)	0.53 (1.8)	0.573
hGDQS	11.32 (4.5)	12.09 (4.4)	11.48 (4.5)	<0.001
hGDQS-	2.09 (1.8)	2.24 (1.9)	2.12 (1.8)	0.039
hGDQS+	9.31 (4.1)	9.94 (4.0)	9.44 (4.1)	<0.001
MFGA	0.44 (0.1)	0.46 (0.1)	0.45 (0.1)	<0.001
MAR	0.87 (0.1)	0.88 (0.1)	0.87 (0.1)	<0.001

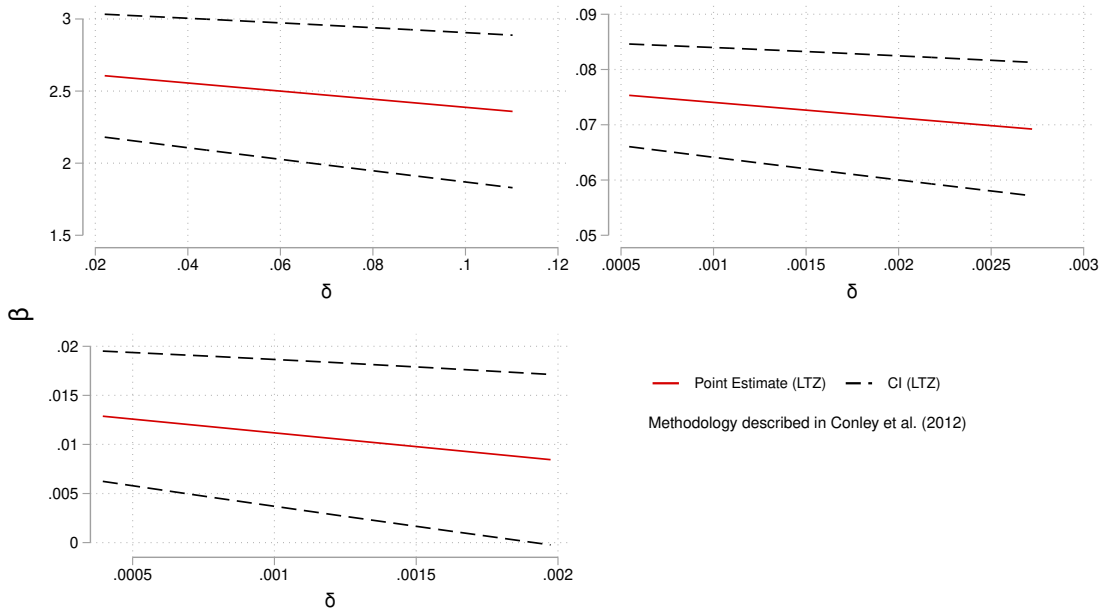
Note: hGDQS = household Global Diet Quality Score, MFGA = Mean food group adequacy, MAR = Mean Adequacy Ratio.

Several covariates provide additional insight into the relationship between income and diet quality (figure VII). In the first stage, years of schooling completed by the household head is positively associated with the log of total expenditure per adult equivalent, but its second-stage coefficient is small and statistically insignificant, suggesting that education improves diet quality primarily through earnings and resources rather than through direct knowledge. A small positive effect for MFGA may indicate some effect of education on knowledge or prioritization of a balanced diet. Household composition shows a consistent pattern whereby larger numbers of all groups, and particularly working age males and young children, are associated with lower expenditures per adult equivalent in the first stage. When income is instrumented, these demographic groups are significantly positively associated with hGDQS. This pattern suggests households may prioritize diverse and recommended food groups for young children and working-age men. Rural residence remains strongly and negatively associated with diet quality even after instrumenting for income, suggesting that there are systematic differences in food environments in rural areas that negatively impact diet quality. Households reporting a larger number of weather-related shocks have significantly lower per-adult expenditures in the first stage, but show higher diet quality in the second stage. This somewhat surprising outcome could reflect the role of government relief efforts or changes in consumption related to repeated climatic shocks. The receipt of free maize is not significantly associated with income in the first stage, but is associated with substantially higher diet quality after instrumentation, consistent with either a direct benefit or an income effect as a result of freeing resources for other foods. This finding is similar for MFGA, although the positive effect

on diet quality is muted, in part due to MFGAs emphasis on proportionality across food groups (figure VIII). These results suggest that income is the dominant driver of diet quality, but that households' demographic structure, rural residence, and the impacts of shocks and in-kind transfers influence how wealth or resources translate into healthier diets.

While diagnostic statistics confirm that the instruments are relevant - the Kleibergen–Paap rk Wald F-statistics far exceed conventional thresholds across all specifications - the exclusion restriction warrants caution. The exclusion restriction fails if the asset index is correlated with unobserved determinants of diet quality. Following Conley, Hansen, and Rossi 2012, I relax the exclusion restriction and generate lower and upper bounds for our coefficients (figure 2.4). Using the local-to-zero approach, I find that a relaxation of the exclusion restriction leads to an estimate of $\beta \approx 1.9 - 2.9$. This indicates that even if the instrument is not strictly exogenous, I still see evidence of a statistically significant effect of income on the hGDQS. I find similar results for MAR and MFGA; the relationship remains statistically significant but becomes even less economically significant in the face of violations of the exclusion restriction.

Figure 2.4: Robustness to relaxation of the exclusion restriction



Source: Authors' calculations following Conley et al. (2012). Notes: Solid lines indicate the point estimate, and dashed lines indicate the confidence intervals estimated using the local-to-zero approach. Beta represents the estimated effect of expenditure on the diet quality outcomes, and delta reflects the extent to which the exclusion restriction may be violated, representing the relationship between the instrument and the error term.

The IV quantile regression results for hGDQS, MFGA, and MAR demonstrate that the relationship between income and diet quality is positive and statistically significant across

the diet quality distribution, with larger coefficients at higher quantiles for hGDQS. This pattern suggests that households with already higher hGDQS scores diets benefit somewhat more from additional income (figure 2.5).[9] For MFGA and MAR, the income effect appears different from estimates at the mean only in the upper quantiles, such that additional income leads to small improvements in adequacy, but with lower gains for those with high existing food group or nutrient adequacy. The muted responsiveness of MFGA and MAR are due in part to the truncated nature of these measures, whereby overshooting recommendations is not penalized differently depending on the magnitude of the excess. Neither MFGA nor MAR can exceed a value of 1 by design. The results of Kolmogorov–Smirnov post-estimation tests show insufficient evidence to reject the null of no effect at all quantiles, for all metrics; however, we cannot reject the null of a constant effect for hGDQS. The apparent upward slope in the plotted coefficients for hGDQS is not statistically significant.

Distribution regression results further highlight where along the diet quality spectrum the relationship with income is largest (figure 2.6). For all metrics, the effect of income on meeting a certain level of diet quality follows an inverted-U shape. The peak at cutoffs in the middle of the distributions indicates that additional income would shift households from moderate to good diet quality the most, with smaller gains for those at the extremes. These patterns suggest that while higher income households surpass intermediate thresholds of diet quality, improving diets among the poorest or most diverse households may require complementary interventions. Notably, the peak for hGDQS lies in the range between the high-risk threshold (scores below 15) while the low-risk threshold (scores of 23 or above) does not exist within this sample.

The semiparametric results support the idea of a nonlinear relationship and flatteningof the relationship between income and diet quality. The relationship between hGDQS and income was visualized using a scatterplot of 28 quantile-spaced bins. Formal tests of the slope provide additional evidence that the association between income and (hGDQS) is monotonically increasing. I reject the null hypothesis of a non-increasing trend ($p < 0.001$) while finding no statistical evidence of a downward-sloping trend ($p \approx 0.2$).

[9] I use the *ivqregress* package in Stata version 19.5.

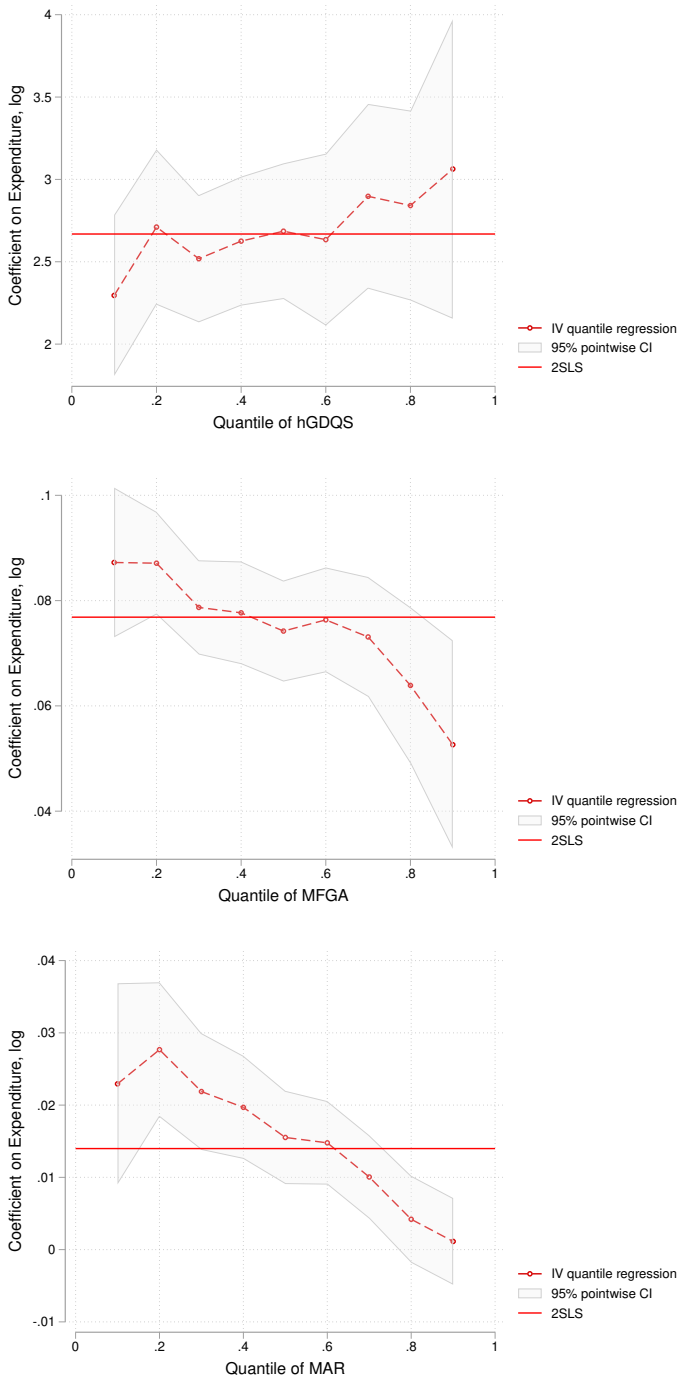


Figure 2.5: Coefficient plots, quantile regression

Notes: Figures show quantile regression coefficient plots estimated using the Stata ivqregress command (dashed red lines) relative to the 2SLS IV coefficient estimated at the mean (solid red line).

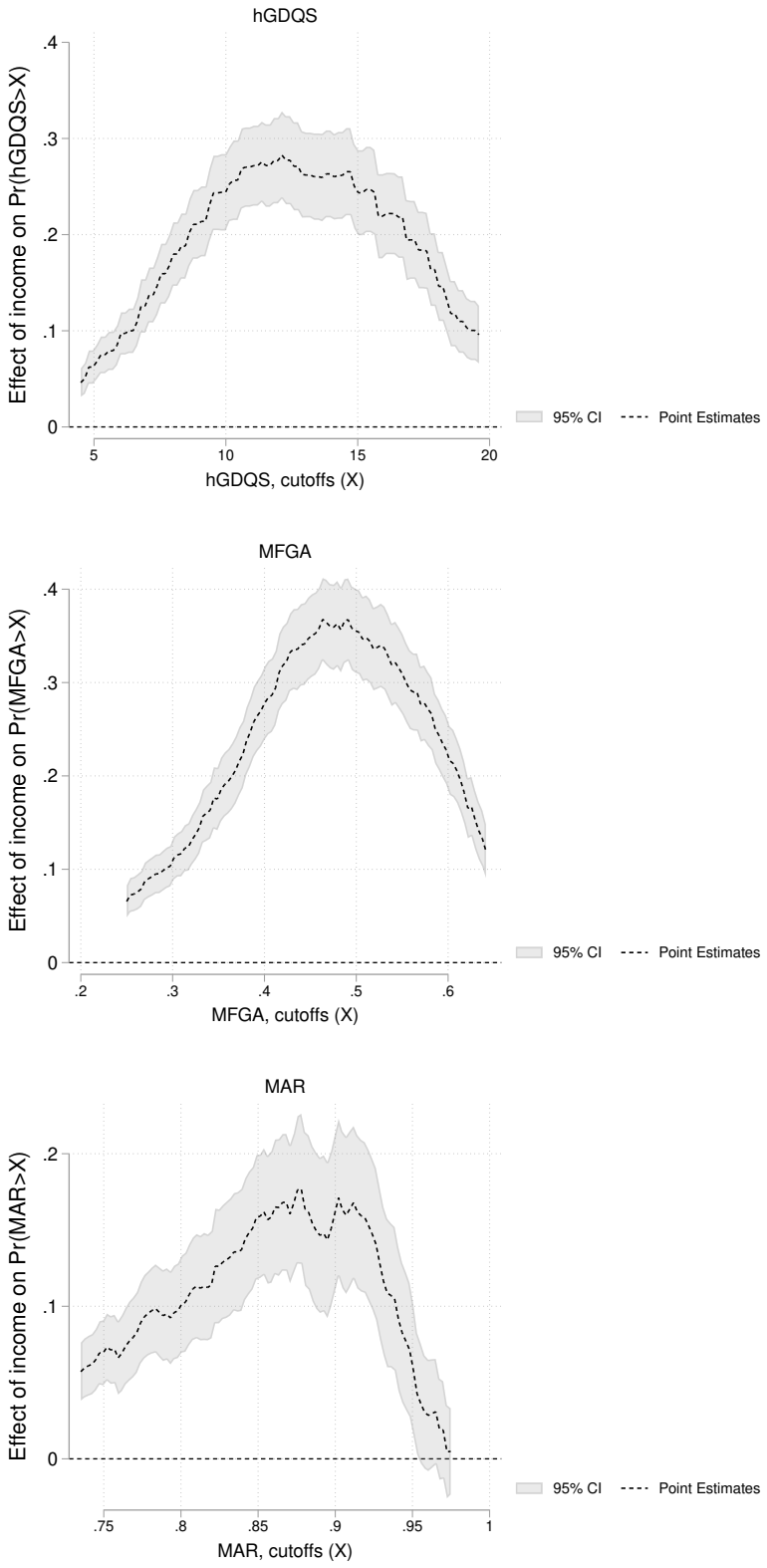


Figure 2.6: Coefficient plots, distribution regressions

Notes: Figure show the estimated marginal effect of logged expenditure (2021 PPP) on the probability of exceeding each possible cutoff value of the diet quality measure, from distribution regressions estimated using a linear probability model at each cutoff with IV specifications instrumenting expenditure.

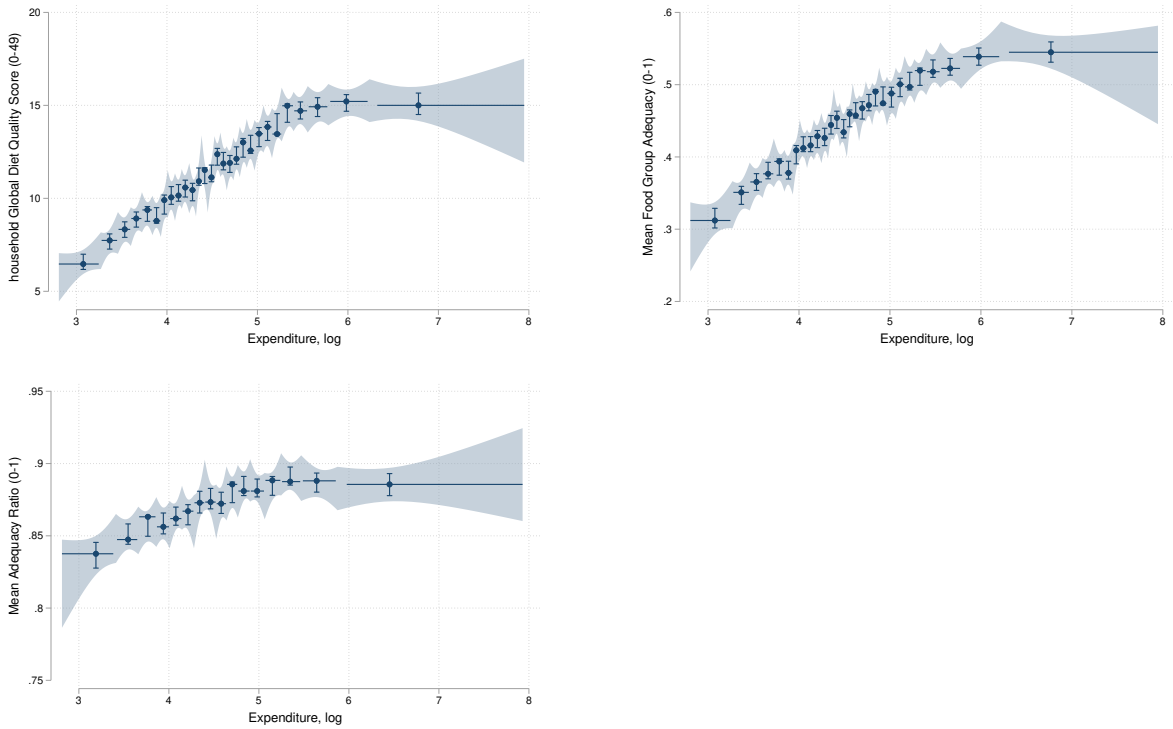


Figure 2.7: Semiparametric regression results

Notes: Binned scatterplots from binsreg. Source: Matias Cattaneo et al. (2024)

2.6 Discussion

I find evidence that among some of the lowest-income households in the world, the relationship between diet quality and income is positive and monotonic. I find evidence of non-linearity, whereby diet quality levels off among wealthier households. Semiparametric estimates suggest that diet quality, measured by the hGDQS and MFGA, is higher among households with greater expenditure until the relationship flattens at the upper end of the income distribution. I do not find evidence to reject the null hypothesis that the relationship between income and any of the diet quality metrics assessed is monotonic.

Higher hGDQS among wealthier households reflects both greater consumption of "healthy" food groups and lower intake of "unhealthy" foods. Consumption of fruits and legumes, nuts, and seeds do not differ significantly across the income distribution, while vegetable consumption appears to have a negative association with income. This departure from dietary recommendations merits further investigation; successful interventions to increase fruit and vegetable consumption remain elusive (Pastori et al., 2024). While higher incomes are associated with shifts away from starchy staples, even the wealthiest households consume more starchy staples than is recommended, as well as oils and fats and discretionary foods like sugar and sweets.

The parametric and semiparametric results indicate that the association is modest. Doubling income is associated with a 2.95-point higher hGDQS from a mean of 11.5, leaving many households in the high-risk range for nutrient inadequacy and diet-related disease. The bounds analysis indicates that these results are robust to plausible violations of the exclusion restriction. Quantile and distribution regressions reveal heterogeneity across the diet quality distribution, with the largest potential gains in diet quality for households around the middle to high end of the distribution.

This study also presents evidence that income-driven improvements depend on household characteristics and contextual factors such as the household's age-sex composition, education levels, access to programs that provide free food, and exposure to weather shocks. Rural residence remains strongly and negatively associated with diet quality after instrumenting for income, suggesting that structural constraints in rural food environments hinder even households with greater resources in choosing healthier diets. Household composition is also important: at higher income levels, households with more young children and working-age men tend to have better diet quality. Education of the household head operates primarily through its correlation with income, although small positive associations with MFGA suggest a possible independent role in promoting balanced diets.

Our results are consistent with the finding that diets improve as incomes increase, such that income transfers and better earnings for the poorest and most vulnerable households are critical to avoiding malnutrition in all its forms. However, our results suggest that large increases in household incomes would be needed to achieve critical gains in diet quality for most Malawian households; my results suggest that a doubling of income would result in scores that still predict a high risk of both undernutrition and diet-related NCDs. Income-driven strategies for improving dietary outcomes like cash transfers or social safety nets are critical to improving diets in Malawi. Nutrition-sensitive social protection, including both

in-kind and cash transfers, can support diet quality, potentially by freeing up resources for foods. More research is needed to understand how to improve consumption of key food groups such as fruits, vegetables, and legumes nuts and seeds.

Finally, I present evidence that for policies and programs aiming to improve diet quality, purely income-based efforts could focus on households with already higher baseline diet quality, where incremental income could be more effectively leveraged for dietary improvements, although this would be logistically difficult. This result is broadly consistent with McCullough et al. 2024, where income elasticities for a Nutrient-Rich Food Index were highest for the two middle income quartiles than for the poorest and wealthiest households in Malawi 2024. Complementary interventions may be needed for other constituencies.

In Malawi, increasing incomes and improving market access to diverse foods are important have been shown to be more effective at increasing dietary diversity than assistance aimed at own-production of diverse foods (Matita et al., 2021). Programs that increase availability and reduce the cost or at least price variability of fruits, vegetables, and legumes nuts and seeds could help reduce gaps between recommended and reported consumption. High seasonal variations in the cost of fruits and vegetables (Bai et al., 2020) and large, negative own-price elasticities suggest that supply-side interventions are critical to increasing fruit consumption. Evidence from India suggests that low-cost pulses alone may not be sufficient for improved consumption (Chakrabarti et al.).

This analysis has several limitations. First, the unbalanced panel hindered the use of panel data methods such that unobserved time-invariant household characteristics may be confounding. Although use of instrumental variables helps mitigate measurement error in this analysis, the exclusion restriction may not hold if the instrument is correlated with unobserved determinants of diet quality, preventing causal inference. Furthermore, precision at the highest income levels is limited due to small sample sizes in the tails of the distribution. Low diet quality among the wealthiest households in the 2010 panel exert influence on the results, and may reflect outdated conditions or poor data quality.

Diet quality is measured using household-level consumption data. The energy-adjusted household consumption per adult equivalent is derived from a 7-day recall, which may mask important differences in intra-household food allocation and individual dietary patterns. While energy adjustment attempts to correct for misreporting, energy adjustment may affect certain food groups or population group responses more than others, resulting in nonclassical measurement error. Finally, the diet quality measures used here — hGDQS and MFGA in particular — have idiosyncratic scoring or calculation rules. Future research should examine these and study whether the metrics are valid for use with household survey data.

Finally, future research should continue to explore how the characteristics of the food environment moderate the association between income and diet quality, track how diet quality varies between contexts at different income levels, and evaluate policies that simultaneously address income and improve access to diverse healthy foods, in particular fruits and vegetables. Understanding how income interacts with structural and behavioral determinants of diet quality will be critical to designing effective interventions for healthier diets in low-income

settings.

Chapter 3

Healthy diets in eight West African countries: Access and preferences

Rachel Gilbert, Hervé Guéné, Harounan Kazianga, William Masters, Mohamed Nana[1]

Abstract

We examine the relationship between income, affordability, and healthy diet consumption in eight WAEMU countries using household survey data. We estimate an Exact Affine Stone Index (EASI) demand system for nineteen goods, including sixteen food groups that correspond to recommendations in dietary guidelines. We analyze how consumption patterns and diet quality vary with the cost and affordability of healthy diets. We find that while greater affordability of healthy diets is associated with higher diet quality, affordability of least-cost diets does not translate into proportional increases in consumption of recommended food groups, like fruits and vegetables. Income elasticity estimates are larger for "other foods" and non-food items than healthy diet components, indicating that additional income is will be allocated outside the recommended food basket, particularly for wealthier households in urban areas. These findings suggest that using policy tools such as income transfers may not be enough to address low diet quality in the region. Alternative policies, such as in-kind transfers of healthy foods or vouchers targeting specific foods, could be more effective but may be logistically challenging.

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3.1 Introduction

Low-quality diets are the largest single preventable cause of disease and premature mortality in the world (Murray et al., 2020). Low-quality diets are caused either by lack of access and unaffordability of the foods needed for health, or by other factors that determine choice among affordable foods such as taste and preferences, cultural aspirations or constraints on meal preparation (Masters et al., 2022a). Diet-related diseases are particularly pronounced in low- and middle-income countries, where rapid urbanization and economic transitions are reshaping food systems and dietary patterns (Popkin et al., 2020a).

Improving diet quality is particularly acute in sub-Saharan Africa, where undernutrition coexists with rising obesity and non-communicable diseases, creating a "double burden" of malnutrition (Popkin et al., 2020a). This nutritional transition is occurring against climate change, population growth, and economic instability, further complicating efforts to ensure food security and promote healthy diets (Fanzo et al., 2018). West Africa, in particular, faces unique challenges due to its rapidly growing population, urbanization, and changing food environments (Staatz and Hollinger, 2016). Understanding the key factors shaping food and dietary choices in the region is essential for formulating effective strategies to address low-quality diet-induced malnutrition.

In this paper, we use household survey data from the eight WAEMU countries (Benin, Burkina Faso, Guinea-Bissau, Ivory Coast, Mali, Niger, Senegal, and Togo) to construct various indicators of diet quality, as well as the cost and affordability of healthy diets. We use sixteen food groups that map onto the six recommended food groups from the Healthy Diet Basket standard used for monitoring least-cost healthy diets, adding three non-food groups to explore the relationship between food and non-food consumption. We estimate a demand system for these groups using the Exact Affine Stone Index (EASI) model, which is flexible and accounts for preference heterogeneity. We provide new estimates of food demand and its relationship to the cost, affordability, and consumption of healthy diets using recent household surveys and local prices in these countries. The countries share harmonized data collection systems that span a wide range of rural and urban environments, providing an unparalleled opportunity to describe variation in food access and the role of prices and income in the intake of healthy diets in West Africa.

The significance of this research lies in its potential to inform evidence-based policies and interventions that aim to improve nutrition and food security in the region. By focusing on the WAEMU countries, we can examine the dynamics of food demand and diet quality within a shared economic framework, while also taking into account the diverse agricultural, cultural, and socioeconomic contexts of each nation. This approach allows for both country-specific insights and broader regional implications, contributing to a more nuanced understanding of food systems in West Africa. The first question for which our study will provide new evidence is how various household characteristics and other factors account for differences in diet quality when controlling for market prices and total household income. This question is particularly relevant in the context of West Africa, where a significant portion of the population relies on smallholder agriculture for both income and subsistence (FAO, 2015). Understanding the dynamics between household characteristics, market reliance, and diet quality can

inform targeted interventions to improve nutrition across diverse population segments. To answer this research question, we will build on the rich history of estimating demand systems for essential nutrients in Africa (Pitt, 1983; Ecker and Qaim, 2011; McCullough et al., 2022).

The second question we address is the relationship between a household's actual consumption and its access to healthy diets. Here, food access is measured as the degree to which a household's available income for food exceeds the daily cost of the least expensive items in local markets that would be needed to meet dietary guidelines, and non-food needs. This method of measuring food access, known as the cost and affordability of healthy diets (CoAHD), has recently been adopted by the Food and Agriculture Organization (FAO) and the World Bank as a key metric of global food security (FAO; IFAD; UNICEF; WFP; WHO, 2024b).

The CoAHD approach represents a significant advancement in measuring food security and access to nutrition. It moves beyond simplistic calorie-based measures to consider the full spectrum of nutrients required for a healthy diet. By focusing on the least-cost items that meet dietary guidelines, this method provides a more realistic assessment of the economic barriers to achieving good nutrition.

The development of the CoAHD metric builds on a pilot application in Ghana and Tanzania (Masters et al., 2018) and least-cost diet analyses extended to Tanzania, Malawi and Ethiopia (Bai et al., 2022; Schneider and Herforth, 2020b). It was further adapted for worldwide monitoring in work for the FAO (Herforth et al., 2025, 2022c) to inform the UN agencies' flagship annual report, "The State of Food Security and Nutrition in the World" (FAO; IFAD; UNICEF; WFP; WHO, 2024b). Our study will contribute to this growing body of literature by applying CoAHD in the context of the WAEMU countries.

In this paper, we compare the consumption of food by households with their access to food, identifying the degree to which greater access is actually associated with higher quality of diet. This comparison is crucial for understanding the complex relationship between economic access and dietary choices. It allows us to explore the extent to which improving affordability translates into actual improvements in diet quality, and to identify potential barriers or facilitators in this relationship.

We hypothesize that improved affordability is associated with consumption of healthier diets for rural and lower-income households in the region. This hypothesis is based on the assumption that economic constraints are a primary barrier to achieving a nutritious diet for these households. As affordability improves, we anticipate an increase in the consumption of nutrient-dense foods, including fruits, vegetables, and animal-source proteins.

For urban and higher-income households, we hypothesize that improved affordability allows increased consumption of discretionary foods that may displace low-cost healthy items such as vegetables, pulses, and whole grains. Instead, these households may substitute more desirable but not necessarily healthy items, such as refined grains and more oils and fats, as well as sweet and salty foods, than would be needed for a healthy diet. This hypothesized pattern suggests an inverted U relationship between affordability and diet quality. At the lower end of the income spectrum, greater purchasing power allows for healthier diets among the lowest-income households. However, at sufficiently high incomes, food choice is driven by

other factors such as taste or convenience, cultural aspirations, and meal preparation costs. This dietary transition has been extensively studied in higher-income countries, with only suggestive evidence for Africa (Masters et al., 2022a; Reardon et al., 2021b).

Our study aims to provide robust evidence for this dietary transition in the West African context. By examining the relationship between affordability and diet quality across different income levels and urban-rural divides, we can shed light on the nuanced ways in which economic development and increased food access impact nutritional outcomes. This understanding is crucial for designing effective policies and interventions that not only improve food affordability but also promote the consumption of healthy diets across all segments of the population.

The implications of this research extend beyond academic interest. By providing a comprehensive analysis of food demand, affordability, and diet quality in West Africa, our study can inform a range of stakeholders:

Policymakers can use our findings to design more targeted and effective food security and nutrition policies. Development agencies can leverage our insights to tailor their interventions to the specific needs and challenges of different population subgroups. Agricultural planners can use our results to better align production strategies with nutritional needs and market demands. Public health officials can draw on our findings to develop more effective nutrition education and behavior change programs.

3.2 Methods

3.2.1 The EASI Demand System

We use the "Exact Affine Stone Index" (EASI) model introduced by Lewbel and Pendakur (2009). The EASI model generalizes a class of demand systems, including the "Almost Ideal Demand System" (Deaton and Muellbauer, 1980), where household budget allocations are explained by real expenditures and prices. In particular, the EASI demand system offers two main advantages that we exploit in this study. First, the model allows all two-way interactions between prices, expenditures, and household characteristics. Second, it allows for higher-order polynomials of real expenditures, thus leading to more flexible Engel curves. Finally, a useful property is that the error terms can be interpreted as unobserved preference heterogeneity. To illustrate, suppose two households with identical observables (income and household composition) that face the same prices. The household with a stronger but unobserved preference for vegetables will allocate a larger portion of its expenditures to vegetables compared to the other. The former household is also more affected by a change in vegetable prices, leading to a larger income effect. This is particularly relevant in the context of healthy diets, where preferences for nutrient-dense foods may vary widely across households, holding everything else constant.

The exposition of the EASI model follows Lewbel and Pendakur (2009) and Pendakur (2009). We start with a flexible expenditure function for the household, which returns the minimum monetary amount the household must spend to achieve a certain level of utility u given prices

p and household characteristics **z**. Instead of explicitly modeling a utility function, Lewbel and Pendakur (2009) express utility u as a function of observables. This implicit utility y does not equal u but is one possible cardinalization of u without altering the ordinal structure. Substituting y into the Hicksian demand function obtained through Shephard's Lemma yields implicit Marshallian demand functions dependent on observables and parameters to be estimated (Shephard, 1954).

Lewbel and Pendakur (2009) propose the following cost function for empirical applications:

$$\begin{aligned}\ln C(\boldsymbol{p}, u, \boldsymbol{z}, \varepsilon) = u + \sum_{j=1}^{J}\left[\left(\sum_{r=1}^{R} b_r^j u^r + \sum_{t=1}^{T} g_t^j z_t + \sum_{t=2}^{T} h_t^j z_t u\right)\ln p^j\right] \\ + \frac{1}{2}\sum_{j=1}^{J}\sum_{k=1}^{J}\sum_{t=1}^{T} a^{jkt} z_t \ln p^j \ln p^k \\ + \frac{1}{2}\sum_{j=1}^{J}\sum_{k=1}^{J} b^{jk} \ln p^j \ln p^k u + \sum_{j=1}^{J} \varepsilon^j \ln p^j.\end{aligned} \tag{3.1}$$

The cost for a household i (index dropped for clarity) to consume a bundle of J goods is expressed as a function of utility u and its R polynomials, T characteristics $\boldsymbol{z}$, goods-specific prices $\boldsymbol{p}$, and goods-specific cost shifters (unobserved preference heterogeneity) ε. Applying Shephard's Lemma to equation (3.1), setting $\ln C(\boldsymbol{p}, u, \boldsymbol{z}, \varepsilon) = \ln x$, and substituting implicit utility y for u gives the implicit Marshallian demand system as:

$$\begin{aligned}w^j = \frac{\partial \ln C(\boldsymbol{p}, u, \boldsymbol{z}, \varepsilon)}{\partial \ln p^j} = \sum_{r=1}^{R} b_r^j y^r + \sum_{t=1}^{T} g_t^j z_t + \sum_{t=2}^{T} h_t^j z_t y \\ + \sum_{k=1}^{J}\sum_{t=1}^{T} a^{jkt} z_t \ln p^k + \sum_{k=1}^{J} b^{jk} \ln p^k y + \varepsilon^j,\end{aligned} \tag{3.2}$$

with y defined as:

$$y = u = \frac{\ln x - \sum_{j=1}^{J} w^j \ln p^j + \frac{1}{2}\sum_{j=1}^{J}\sum_{k=1}^{J}\sum_{t=1}^{T} a^{jkt} z_t \ln p^j \ln p^k}{1 - \frac{1}{2}\sum_{j=1}^{J}\sum_{k=1}^{J} b^{jk} \ln p^j \ln p^k}. \tag{3.3}$$

Equation (3.2) is the system of equations to be estimated. Budget shares w^j of goods category j are expressed as linear functions of parameters $b_r^j, g_t^j, h_t^j, a^{jkt}$, and b^{jk}. ε^j represents the unobserved preference parameter (i.e., the error term), with $E[\varepsilon] = \mathbf{0}$. Note that in this notation, the first element of the household characteristics vector $\boldsymbol{z}$ is $\mathbf{1}$. Thus, the first element of the parameter vector $\boldsymbol{g}$ is the constant, and the elements a^{jkt} capture own-price effects. Slutsky symmetry is imposed by setting constraints such that $a^{jkt} = a^{kjt}$ and $b^{jk} = b^{kj}$.

Hicksian (compensated) price semi-elasticities of budget shares are given by:

$$\frac{\partial w^j}{\partial \ln p^k} = \sum_{t=1}^{T} a^{jkt} z_t + b^{jk} y, \tag{3.4}$$

and elasticities with respect to y, interpretable as real expenditure semi-elasticities of budget shares, by:

$$\frac{\partial w^j}{\partial y} = \sum_{r=1}^{R} b_r^j r y^{r-1} + \sum_{t=2}^{T} h_t^j z_t + \sum_{k=1}^{J} b^{jk} \ln p^k. \tag{3.5}$$

These semi-elasticities can generally be converted into ordinary elasticities of budget shares by dividing by the average budget share of the respective population.

The demand system defined by equation (3.2) is endogenous since the budget shares $w^j, j = 1, \ldots, J$ appear on the right side of the equations through the construction of y in equation (3.3). We follow Lewbel and Pendakur (2009) and instrument y by $\ln x$ adjusted by a modified Stone price index, wherein $\bar{w}_j$, the sample-average budget share for food group j, substitutes for w_j:

$$\hat{y} = \ln x - \sum_{j=1}^{J} \bar{w}^j \ln p^j.$$

The system is then estimated iteratively: starting with this initial instrument, we apply 3SLS with the instrumented values of y and its polynomial and interaction terms. After each iteration, the fitted values are used to update the implicit utility measure according to equation (3), incorporating the price adjustment terms $\sum_{l=0}^{L} z_l p' A_l p/2$ in the numerator and $1 - p' B p/2$ in the denominator. This updated y is then used to construct new instruments for the next iteration, and the process continues until convergence is achieved, typically requiring only a few iterations. Throughout this iterative procedure, we impose cross-equation restrictions for adding-up, homogeneity, and Slutsky symmetry.

Our main results control for cluster (or community) fixed effects using the correlated random effects (CRE) (Mundlak, 1978; Wooldridge, 2019). This method augments the demand system by including cluster-specific means of all time-varying covariates—prices, household expenditure, and demographic characteristics—as additional controls. By decomposing variation into within-cluster and between-cluster components, this approach allows identification of demand parameters from within-cluster variation while controlling for time-invariant community characteristics such as local market structures, infrastructure quality, and cultural preferences[2].

Another potential issue is the presence of zeros in the dependent variables, which can occur for several reasons, including infrequent purchases (especially when combined with short recall periods) and true corner solutions. While methods have been proposed to address this issue (e.g., Heien and Wesseils, 1990; Shonkwiler and Yen, 1999), Deaton (1997) and

[2] As a robustness checks, we also estimate specifications that control for fixed effects at higher geographic divisions (region and district levels) and report the implied elasticities in the Figures 7a-10b in the Appendix. These elasticities are generally larger in magnitude but have the same signs as our main results.

Gibson (2019) have noted that if the interest is in average responses (including households who report positive and zero consumption for a given good), adjusting for sample selection or censoring may not be necessary. We follow this recommendation and do not correct for the zeros in our dependent variables.

Finally, we construct community Stone price indices at the food group level, using the granular food items as elements. Specifically, the natural log of the Stone price index for community c, food group $j(j = 1, \ldots, J)$, in period t is calculated as

$$\log\left(p_{cjt}\right) = \sum_{g=1}^{G} w_{cgt} \log\left(p_{cgt}\right)$$

where G is the number of items in group j, w_{cgt} is the budget share of good g in group j for community c at time t, and p_{cgt} is the median of unit price of item g in community c at time t.

3.2.2 Cost and affordability of healthy diets

To distinguish access to healthy diets from other determinants of diet quality, we identify the least expensive combination of locally available foods from each market that would meet dietary guidelines and compare that hypothetical diet cost to each household's actual food expenditure and other metrics of real income and wealth. The least-cost modeled diet at each location provides a benchmark of what could be purchased if a consumer sought only to meet their health needs, and they could observe how food composition relates to health. In practice, people cannot directly observe the healthiness of food and people also have other objectives in addition to health, but there is abundant evidence that historical societies shifted towards healthier diets over time as their incomes rose (Fogel, 2004; Deaton, 2013), even as modern societies often shift towards less healthy diets with higher incomes (Masters et al., 2022a).

To construct the benchmark least-cost healthy diets at each location, we use the method developed by Herforth et al. (2020, 2022c) and adopted by the World Bank and the United Nations for monitoring the access pillar of global food security. For each time t and location or community c for which we have a retail price p for food item g, we start by converting all retail prices into a price per kilocalorie of edible food:

$$k_{tcg} = p_{tci} e_g / ep_g \tag{3.6}$$

where p_{tcg} is the retail price per kilogram, e_g is the energy density of food g per kilogram of edible portion, and ep_g is the edible fraction. Then we calculate the cost per day of each food group j in time t and location l as:

$$C_{tcj} = \min\left(\sum_{g=1}^{n_j} k_{tcg} * t_j / n_j)\right) \tag{3.7}$$

where t_j is the target quantity in kilocalories of food group j and n_j is the number of items recommended in food group j. The target quantities and number of foods recommended per food group are found in table 3.1.

Table 3.1: Healthy Diet Basket composition

Food group	No. of foods selected	Dietary energy (kcal)	Proportion of energy content
Starchy staples	2	1160	0.498
Oils and fats	1	300	0.129
Vegetables	3	110	0.047
Fruits	2	160	0.069
Legumes, nuts, and seeds	1	300	0.129
Animal source foods	2	300	0.129
Total	**11**	**2330**	**1.000**

Source: Herforth et al. (2022c)

For example, in food group j=1, starchy staples, the cost per food group is calculated as:

$$Cost_1 = \min \left\{ \sum_{g=1}^{2} k_g(1160/2) \right\} \tag{3.8}$$

where the food group cost is the sum of the two least-expensive starchy staples in terms of cost per day, based on the price per calorie and an equal allocation of the food group calorie target (1160 kcal per day). Rank-order optimization is used to select the least-cost items. Finally, the cost of a healthy diet is calculated as:

$$CoHD_{tc} = \sum_{j=1}^{6} C_{tcj}, \tag{3.9}$$

The cost of a healthy diet, $CoHD_{tc}$, thus achieves diversity within and across food groups while maintaining energy balance, resulting in the selection of eleven items across six food groups, totaling 2330 calories per person per day. CoHD is calculated for each time and location, and thus each household i living in community c is assumed to face the cost associated with that community. For this analysis, we use median unit prices at the lowest geographic level for which there are five or more observations for food item g as an estimate of the retail price.

Affordability of a healthy diet is a binary indicator calculated for each household i by comparing total consumption expenditure y in adult equivalent terms to the least-cost modeled diet plus an allowance for non-food expenditure FAO; IFAD; UNICEF; WFP; WHO (2024b).

Non-food needs are defined by countries' own non-food poverty lines. [3] If a household spends less than this benchmark, the household is considered unable to afford a healthy diet.

$$A_{htl} = \begin{cases} 1 & \text{if } y_{itc} \geq (CoHD_{tc} + nf_{tn}), \\ 0 & \text{if } y_{itc} < (CoHD_{tc} + nf_{tn}) \end{cases} \tag{3.10}$$

We also calculate the "affordability gap" as the difference between total expenditure per adult equivalent and the cost benchmark. All values are presented in 2021 Purchasing Power Parity (PPP) terms for comparability across countries and survey rounds. Local currency units were adjusted using the monthly national Consumer Price Index (CPI).

3.2.3 Diet quality metrics

Three metrics capture various dimensions of diet quality: diet-related risk factors, proportionality of food groups, and nutrient adequacy. A household-level Global Diet Quality Score (hGDQS) serves as a composite measure of the risk of poor diet quality by scoring the consumption of healthy and unhealthy food groups. Mean food group adequacy (MFGA) is based on the proportionality of calories across food groups as recommended in food-based dietary guidelines. Mean nutrient adequacy (MNA) is a measure of nutrient adequacy that has been validated and widely used as an indicator of individual-level diet quality. [4] All diet quality metrics are calculated using survey data on the quantity of food consumed by household members over the seven days prior to the interview. All food consumption is converted to kilograms using non-standard unit conversion factors provided by market surveys done concurrently with the household surveys. Kilograms of food are then converted to calories using food composition data (Vicent, A et al., 2020; USDA Agricultural Research Service, 2016b). Food consumption is energy-adjusted to account for measurement error in reporting of total intakes (National Cancer Institute).

The Global Diet Quality Score is a food group-based metric developed to assess the risk of poor diet quality, including risk factors for nutrient deficiency and chronic disease in low- and middle-income countries (Bromage et al., 2021; Intake, 2021, 2022; Miller et al., 2020). While GDQS was validated for individual-level dietary recall data, recent work has used 7-day household recall data to calculate a modified GDQS (Ahmed et al., 2022b; **?**). This study uses adult equivalent estimates from household intakes to calculate what we refer to as a household Global Diet Quality Score (hGDQS).

Mean food group adequacy (MFGA) measures the calorie consumption across food groups relative to recommendations in food-based dietary guidelines. As with the least-cost modeled diets, we use the Healthy Diet Basket as the reference guideline (table 3.1). Example diets and their resulting MFGA scores are demonstrated in table 3.2. Example 1 illustrates a uniform deficiency across food groups. In Example 2, 570 calories of sugar-sweetened beverages or

[3] In the absence of national non-food poverty lines, we use the median non-food expenditure nf_{trcq} of households in quintile 3 q of total expenditure, by country n and region$r$.

[4] MNA is referred to as Mean Adequacy Ratio in the nutrition literature, but is referred to as MNA for clarity of acronyms.

other discretionary foods replace starchy staples. In Example 3, 570 calories of discretionary food displaces legumes, nuts, and seeds (LNS), and fruits and vegetables (F&V). In example 4, LNS and F&V are displaced by starchy staples rather than discretionary foods.

Table 3.2: Mean food group adequacy, illustrated with examples of dietary patterns

	Food group rec.		Ex 1		Ex 2		Ex 3		Ex 4.	
Food group	Calories	Deficiency	Calories	Deficiency	Calories	Deficiency	Calories	Deficiency	Calories	Deficiency
Starchy staples	1160	0.000	876	-0.245	590	-0.491	1160	0.000	1730	0.000
Oils and fats	300	0.000	227	-0.245	300	0.000	300	0.000	300	0.000
Fruits	160	0.000	121	-0.245	160	0.000	0	-1.000	0	-1.000
Vegetables	110	0.000	83	-0.245	110	0.000	0	-1.000	0	-1.000
LNS	300	0.000	227	-0.245	300	0.000	0	-1.000	0	-1.000
ASF	300	0.000	227	-0.245	300	0.000	300	0.000	300	0.000
Discr.	0	-	570	-	570	-	570	-	0	-
6-group total	2330	0.000	1760	-0.245	1760	-0.082	1760	-0.500	2330	-0.500
Mean adequacy	1.000		0.755		0.918		0.500		0.500	
Intake per day	2330		2330		2330		2330		2330	

Note: Food group recommendations are from the Healthy Diet Basket. LNS = Legumes, nuts, and seeds; ASF = animal-source foods, Discr. = discretionary foods. The 6-group total is the sum of all six Healthy Diet Basket food groups, excluding discretionary foods. The deficiency is the difference between the target calories per food group and the energy-adjusted consumption of that food group for each household.

Mean nutrient adequacy is used to measure the nutritional adequacy of an individual's diet by comparing nutrient intake to recommended intakes. We calculate mean nutrient adequacy as the average of Nutrient Adequacy Ratios (NAR) for 19 nutrients: carbohydrates, protein, lipids, vitamin A, vitamin C, vitamin E, thiamin, riboflavin, niacin, vitamin B6, vitamin B12, calcium, copper, iron, magnesium, phosphorus, and zinc. Recommended intakes are determined by combining the nutrient needs of each household member, taking into account their age and sex. Intakes are derived by matching each food a household reported consuming to its nutrient composition using Food Composition Tables (Vicent, A et al., 2020; USDA Agricultural Research Service, 2016b). MNA is an average of the individual Nutrient Adequacy Ratios (NAR), each of which is capped at 1. [5] We exclude nutrients for which there is no Recommended Dietary Allowance (RDA), for which there is only an Adequate Intake, or for which data is not commonly reported in food composition tables.

3.3 Surveys and Descriptive Statistics

3.3.1 Surveys

The study uses nationally representative household survey data matched to local market prices for all WAEMU countries (Benin, Burkina Faso, Cote d'Ivoire, Guinea Bissau, Mali, Niger, Senegal and Togo), collected in 2018 and 2021. The first round surveys were conducted from 2018 to 2019 in two waves in each country, forming pooled cross sections that span the pre- and post-harvest seasons of each location. The second round surveys were fielded in

[5] MNA is the same as a Mean Adequacy Ratio. We refer to it as MNA for consistency with the measure of mean food group adequacy.

2021 and 2021, and followed the same pattern, interviewing the same number of households in the pre-and post-harvest seasons.

Questionnaires and other aspects of data collection were based on the Living Standard Measurement Surveys (LSMS) funded by the World Bank, including a standardized household consumption and expenditure module. An extensive community-level survey was also administered to record data on the prices of food items at local markets, as well as public services such as roads and electricity. The survey sample selection occurred in two stages, providing a nationally representative set of clusters (or villages) randomly sampled in the first stage, and households within clusters randomly selected in the second stage.

The consumption module included an extensive list of food and non-food goods. The food consumption module comprised quantities consumed for 148 food items over the seven days preceding the interview. The questions were designed to capture the full range of items consumed, including packaged and processed foods as well as food away from home. The non-food module consisted of 90 non-durable items. We aggregate these items into 19 groups: 16 food categories and 3 non-food categories. The food categories include: (1) rice, (2) traditional cereals, (3) wheat, (4) roots and tubers, (5) oil and butter, (6) fruits, (7) dark green leafy vegetables, (8) other vegetables, (9) legumes nuts and seeds (whole), (10) legumes nuts and seeds (processed), (11) red meat, (12) poultry, (13) fish, (14) dairy, (15) eggs, and (16) other foods. We also aggregate around 90 individual non-durable non-food items into three groups: (17) household goods, (18) services, and (19) other non-durables. These 19 aggregated food and non-food goods form the basis of our demand system analysis.

Table 3.3 summarizes the sample sizes. There are 59,318 sampled households in the first round, about 58% of whom are in rural areas. Approximately the same number of households (59,875) were interviewed in the second round, with an identical breakdown between rural and urban areas. Sample size varies by country, from approximately 12,990 households per round in Côte d'Ivoire to 5,351 in Guinea-Bissau.

Table 3.3: Sample Size

Country	First Round	Second Round	Panel	% panel
Benin	8,012	8,032	6,889	86.0%
Burkina Faso	7,010	7,176	3,228	46.0%
Cote d'Ivoire	12,992	12,969	9,211	70.9%
Guinea-Bissau	5,351	5,351	4,897	91.5%
Mali	6,602	6,143	5,393	81.7%
Niger	6,024	6,622	5,055	83.9%
Senegal	7,156	7,120	6,127	85.6%
Togo	6,171	6,462	5,301	85.9%
Total	59,318	59,875	46,101	77.7%

The percentage of households that were successfully re-interviewed in the second wave. presented in the last column, varies significantly across countries. The highest re-interview rates were observed in Guinea-Bissau (91.5%) and Benin (86.0%), while the lowest rates were

recorded in Burkina Faso (46.0%). This disparity can be partly attributed to deteriorating security conditions in certain regions, where conflict and instability may have induced population displacements and limited enumerators' ability to reach many households.

3.3.2 Descriptive Statistics

The distribution of household expenditures in rural and urban regions, as seen in Table 3.4, demonstrates significant disparities in consumption allocation across income levels. In rural areas, cereals and tubers (rice, traditional cereals, wheat, and roots and tubers) constitute a substantial portion of household expenditures, with the lowest-income quartile (Q1) dedicating 29.8% of their total budget to these food groups (rice 8.2%, traditional cereals 15.8%, wheat 1.1%, and roots and tubers 4.7%). This proportion declines consistently with income, reaching 23.5% in the highest quartile (Q4). In contrast, budget shares of animal source foods (red meat, poultry, fish, dairy, and eggs) increase with income, suggesting these may be luxury commodities in rural settings. For example, the combined budget share allocated to these animal products increases from 8.8% in Q1 to 15.5% in the top quartile.

Table 3.4: Average budget share in total expenditures

Item	Rural					Urban				
	Q1	Q2	Q3	Q4	Price	Q1	Q2	Q3	Q4	Price
Rice	0.082	0.097	0.098	0.084	434.77	0.079	0.080	0.075	0.063	456.47
Traditional cereals	0.158	0.119	0.091	0.066	389.57	0.066	0.046	0.036	0.024	393.71
Wheat	0.011	0.015	0.019	0.027	932.53	0.021	0.027	0.032	0.038	795.23
Roots and tubers	0.047	0.050	0.055	0.058	609.72	0.036	0.036	0.036	0.034	531.28
Oil and butter	0.033	0.034	0.034	0.037	1017.42	0.033	0.032	0.033	0.037	1037.27
Fruits	0.026	0.028	0.029	0.035	903.75	0.024	0.024	0.025	0.032	548.44
Dark green leafy vegetables	0.020	0.014	0.011	0.009	602.18	0.012	0.009	0.008	0.006	578.14
Other vegetables	0.050	0.050	0.050	0.051	678.40	0.056	0.057	0.058	0.057	690.01
LNS (whole)	0.024	0.024	0.024	0.023	850.69	0.015	0.012	0.011	0.010	852.63
LNS (processed)	0.008	0.009	0.010	0.010	1086.78	0.009	0.009	0.008	0.007	990.28
Red meat	0.021	0.033	0.043	0.053	2173.43	0.028	0.045	0.052	0.058	2249.51
Poultry	0.008	0.013	0.016	0.021	2607.32	0.008	0.012	0.015	0.025	2490.85
Fish	0.044	0.045	0.047	0.051	1615.29	0.051	0.051	0.052	0.068	1522.91
Dairy	0.013	0.017	0.022	0.027	1879.76	0.013	0.018	0.023	0.029	2010.66
Eggs	0.002	0.002	0.002	0.003	2073.05	0.004	0.005	0.005	0.006	1625.94
Other foods	0.198	0.192	0.193	0.206	611.78	0.270	0.259	0.258	0.241	466.18
Household goods	0.219	0.219	0.214	0.194	69.05	0.235	0.234	0.225	0.211	80.28
Services	0.019	0.018	0.020	0.023	80.24	0.020	0.021	0.025	0.031	93.04
Other non-durables	0.018	0.021	0.022	0.023	68.80	0.019	0.020	0.022	0.023	77.04
N (total)	16326	16326	16326	16325		11746	11745	11746	11745	

Note: LNS = Legumes, nuts, and seeds.

Urban households demonstrate a distinct expenditure pattern, with "other foods" representing the largest single category across all income brackets, accounting for 27.0% of expenditures in Q1 and declining slightly to 24.1% in Q4. All foods that are not explicitly needed as part of a healthy diet are included in the "other foods" category, including things like spices and condiments, which are discretionary but not excluded for health reasons, as well as those that are specifically not recommended as part of a healthy diet (e.g., processed meats, foods

high in saturated fat, or sugar-sweetened beverages). Similar to rural areas, animal source foods show a distinct income gradient in urban regions, with their combined proportion (red meat, poultry, fish, dairy, and eggs) increasing from 10.4% in the first quartile to 18.6% in the fourth quartile. Notably, fish constitutes the largest animal protein expenditure across all income quartiles in urban areas, ranging from 5.1% in Q1 to 6.8% in Q4. The percentage of expenditure on cereals and tubers (rice, traditional cereals, wheat, and roots and tubers) decreases with income, from 20.2% in Q1 to 15.9% in Q4, with traditional cereals showing the steepest decline (from 6.6% to 2.4%).

A consistent pattern in both rural and urban areas is the declining budget share allocated to household goods as income increases. For rural households, the budget allocated to household goods decreases from 21.9% in the first quartile to 19.4% in the top quartile. The pattern is similar for urban households, with the budget share allocated to this group of goods decreasing from 23.5% in Q1 to 21.1% in Q4. This suggests that these non-food items constitute a greater share of expenditure among lower-income households in both rural and urban areas.

Examining specific food items reveals interesting consumption patterns. Traditional cereals show the most substantial decrease with rising income in both areas, declining from 15.8% to 6.6% in rural areas and from 6.6% to 2.4% in urban areas. Conversely, wheat consumption increases with income in both regions, rising from 1.1% to 2.7% in rural areas and from 2.1% to 3.8% in urban areas. This suggests a shift from traditional cereals to wheat-based products as incomes rise. Red meat expenditure shows a particularly strong income gradient, more than doubling from Q1 to Q4 in both rural (2.1% to 5.3%) and urban (2.8% to 5.8%) settings.

It is also notable that for both rural and urban households, the budget shares for "other foods" show different patterns. In rural areas, this category shows a slight U-shaped pattern, decreasing from 19.8% in Q1 to 19.2% in Q2 before increasing to 20.6% in Q4. In urban areas, "other foods" gradually decrease across income quartiles from 27.0% in Q1 to 24.1% in Q4. This contrasts with the previous observation that households at higher income levels universally prioritize convenience foods.

The tables also underscore disparities in average prices across rural and urban regions. Most food items are more expensive in urban areas than in rural areas. For instance, rice (456.47 vs. 434.77), wheat (795.23 vs. 932.53), and red meat (2249.51 vs. 2173.43) all cost more in urban regions. However, there are notable exceptions: fruits are significantly more expensive in rural areas (903.75) than in urban areas (548.44), potentially reflecting challenges in rural supply chains for perishable produce. Traditional cereals show similar prices in both areas (393.71 urban vs. 389.57 rural), suggesting efficient markets for these widely consumed staples. These price disparities likely reflect differences in supply chains, transportation costs, and market access between rural and urban regions. It is plausible that the supply of processed foods and vegetables is increasing faster in urban areas due to the growth of small and medium enterprises and peri-urban agriculture (e.g., Reardon et al., 2021a).

We complement the descriptive tables with the Engel curves in figures 3.3, 3.4, 3.5 as well as in Appendix figures 3.17, 3.18, and 3.19. The figures show that the Engel curves for

the food groups exhibit both linear and non-linear polynomial patterns. Specifically, as household expenditures rise, the budget shares allocated to certain food groups increase, others decrease, and some exhibit an initial rise followed by a decline. This diversity in patterns suggests that allowing more flexible Engel curves could provide a more accurate representation of the income effects.

These figures also show that low-income households in rural and urban areas allocate a larger share of their income to vegetables, legumes, nuts and seeds, starchy staples, and household goods than wealthier households. In contrast, they spend less on animal-source foods, fruits, other foods, and non-durables. In urban areas, low-income households allocate a higher proportion of their budget to oils and fats, while wealthier households spend more on these items in rural areas. Additionally, poorer households in rural areas spend more.

3.4 Results and Discussion

3.4.1 Demand System Estimates

We summarize income and price elasticities in Figure 8, with the estimates of rural and urban households shown separately. [6] The figures depict own- and cross-price elasticities in the first nineteen columns and income elasticities in the last column.

All own-price and income elasticities are statistically significant at the 5 percent level, and all income elasticities are positive, confirming that every category is a normal good. In the rural sample, the most income-responsive categories are poultry (2.22), red meat (2.01), eggs (1.61), dairy (1.51), and wheat (1.51), followed closely by roots and tubers (1.35), fruits (1.35), services (1.27) and other non-food goods (1.23). Legumes (1.09) and legume products (1.02) register elasticities essentially equal to one, while the remaining goods—including rice (0.45), traditional cereals (0.44), oil & fats (0.85), vegetables (0.93), fish (0.95) and household goods (0.95)—all lie below unity, indicating a less-than-proportional income response. We observe a similar but somewhat muted pattern in the urban subsample: poultry (1.98), eggs (1.61), red meat (1.48), dairy (1.34), fruits (1.25) and roots (1.25) remain the most income-elastic, with wheat and household goods both just above one (1.03). Income elasticities for other non-food goods (1.39) and services (1.51) also exceed unity. All other food items range from 0.36 (rice) to 0.92 (fish), identifying them as necessities whose consumption grows less than proportionally with income. The estimates indicate that as income rises, rural households disproportionately increase their consumption of animal-source foods (red meat, poultry, dairy, eggs) and processed foods, while consumption of staples and legumes grows at a slower pace than income change. Considering the confidence intervals, our results are generally consistent with recent elasticity estimates in sub-Saharan Africa (e.g., Liverpool-Tasie et al., 2021; McCullough et al., 2022).

The principal diagonal displays own-price elasticities, all of which are negative as expected. For rural households, staples are price inelastic—rice (–0.77), traditional cereals (–0.74), wheat (–0.92) and roots (–0.68) all have elasticities that are less than unity. In contrast,

[6] Figures with the point estimates and the 95% confidence intervals based on bootstrapped standard errors are shown in the Appendix. The bootstrap used 50 replications.

poultry (–1.86), eggs (–1.73) and the "other foods" bundle (–1.12) exceed unity in absolute value, indicating that these goods are price-elastic. In urban areas rice (–0.13), cereals (–0.76), wheat (–0.81) and roots (–0.33) remain inelastic, with poultry (–1.39), eggs (–1.25) and other foods (–1.19) again the most price responsive. In both settings, absolute own-price elasticities are uniformly smaller than the corresponding income elasticities, indicating that consumers adjust more to changes in income than to changes in price.

For all goods categories considered, demand responds positively to income change in rural areas. In urban areas, most goods likewise exhibit positive income elasticities, although a few vary across expenditure quartiles. Using the point estimates and the confidence intervals, we classify goods into luxuries (income elasticity more than 1), necessities (less than 1), and unit-elastic items (around 1). These classifications reveal clear differences between rural and urban households, reflecting distinct consumption patterns and economic behaviors in each setting.

We now turn to cross-price elasticities. In the rural subsample, several off-diagonal coefficients are statistically significant at the 5 percent level. Notable complementarities include rice and wheat (–0.044; 95 % CI [–0.06, –0.03]), wheat and oil & fats (–0.142; [–0.20, –0.08]), oil & fats and fruits (–0.350; [–0.46, –0.24]), fruits and roots (–0.100; [–0.13, –0.07]), green vegetables and wheat (–0.109; [–0.14, –0.08]), legume products and legumes (–0.947; [–0.99, –0.91]), dairy and wheat (–0.046; [–0.06, –0.03]), and fish and rice (–0.194; [–0.25, –0.14]). Significant substitution relationships include traditional cereals with rice (+0.049; [0.01, 0.08]), poultry with green vegetables (+0.115; [0.07, 0.16]) and with vegetables (+0.147; [0.07, 0.23]), fruits with eggs (+0.090; [0.05, 0.13]), red meat with other foods (+0.265; [0.22, 0.31]), household goods with other foods (+0.047; [0.04, 0.06]), and services with other foods (+0.277; [0.12, 0.44]). These limited but meaningful off-diagonal effects indicate that, beyond a few tightly linked complements and substitutes, rural households generally adjust most food categories independently when prices change.

Moving to the urban subsample, several off-diagonal coefficients reach statistical significance at the 5 percent level, revealing both complementarities and substitutions. Notable complements include rice with wheat (–0.116; 95 % CI [–0.150, –0.083]), rice with roots (–0.145; [–0.219, –0.072]), fruits with oil & fats (–0.106; [–0.132, –0.079]), and legume products with legumes (–1.084; [–1.131, –1.037]). Among significant substitutions, traditional cereals and green vegetables register +0.128 ([0.050, 0.206]), fruits and other foods +0.294 ([0.240, 0.348]), poultry and eggs +0.254 ([0.180, 0.328]), and dairy and fruits +0.116 ([0.080, 0.148]). These results indicate that, in urban areas, while most categories move independently, certain staples and oils are tightly linked as complements, and higher-value items tend to substitute for basic cereals and processed foods.

We show elasticities by expenditure quartiles in Figures 9 and 10 for the rural and urban subsamples, respectively. In the rural subsample, own-price elasticities for most basic foods—rice (1.117 vs. 0.226), traditional cereals (0.939 vs. 0.316) and wheat (0.835 vs. 0.961) among them—are statistically indistinguishable between the lowest (Q1) and highest (Q4) quartiles when comparing their overlapping 95 % confidence intervals.[7] Animal-source foods become

[7]Estimates are deemed indistinguishable when their 95 % CIs overlap.

less price-elastic at higher expenditure levels: red meat shifts from 1.167 (Q1) to 1.021 (Q4) and poultry from 2.323 to 1.712. By contrast, oils and fats are more price-elastic among the poorest: 0.421 in Q1 versus 0.253 in Q4. Expenditure (income) elasticities remain broadly stable for staples but vary more for animal-source products: red meat's income elasticity reduces from 2.343 in Q1 to 1.659 in Q4, and fish from 1.032 to 0.865, underscoring greater responsiveness to income changes among lower-spending rural households.

In the urban subsample, the estimates of own-price elasticities are statistically comparable between the lowest quartile (Q1) and the highest quartile (Q4) for most food items. The major exceptions are dairy (-0.933 in Q1 vs -0.810 in Q4), eggs (-1.468 in Q1 vs -1.176 in Q4), and other foods (-1.170 in Q1 vs -1.205 in Q4). Expenditure elasticities also vary between quartiles. Wheat shows higher income elasticity in Q1 (1.298) compared to Q4 (0.871). Poultry demonstrates substantially higher income elasticity in Q1 (2.424) versus Q4 (1.650). Services show similar income elasticity in both quartiles (1.502 in Q1 vs 1.516 in Q4). Other notable differences include red meat (1.753 in Q1 vs 1.273 in Q4) and eggs (1.853 in Q1 vs 1.375 in Q4), both showing considerably higher expenditure elasticity in Q1.

Comparing across geographies within quartiles, Q1 urban households demonstrate higher price sensitivity for rice and vegetables (e.g., rice $\approx$ 0.38 urban vs. 0.24 rural, though not explicitly provided for rural Q1 rice in original text, implied comparison) but lower responsiveness for poultry (1.65 urban vs. 2.32 rural). Income elasticities for poultry and rice are slightly higher for Q1 urban households. By Q4, most rural-urban differences in elasticities become statistically insignificant, with lingering differences for legumes (own-price elasticity $\approx$ 1.03 rural vs. 0.95 urban) and poultry expenditure elasticities (1.78 rural vs. 1.65 urban). The estimated elasticities carry substantial economic implications. The pronounced income responsiveness for animal-source products (e.g., poultry, red meat, eggs) strongly suggests that as household incomes rise, expenditure patterns will disproportionately shift towards these nutrient-dense foods. This signals an ongoing dietary transition, which may harbor both welfare and public health benefits. Conversely, the inelastic demand observed for staple foods underscores their role as fundamental consumption anchors. This implies that price subsidies targeted at staples would likely have limited crowd-out effects on overall caloric intake from other sources.

For a group healthy goods including green vegetables, vegetables and legumes, the own-price in absolute value are higher than income elasticities for the lowest income quartile in both rural and urban areas. This suggests that these goods are more sensitive to price changes than to income changes, indicating that they are more likely to be consumed in response to price reductions rather than income increases, particularly at very low income levels. We observe a similar pattern for rice and traditional cereals for these income groups. Thus, for low-income households, while income support may still be generally effective at increasing consumption for all foods, a price policy appears more effective for a subgroup of foods that are equally critical to a balanced diet.

The nature of cross-price elasticities also offers insights. For instance, the stronger complementarities among items like legumes and oil & fats in rural areas suggest that price variations in one category could significantly influence the consumption of related goods. In contrast, the sparser cross-price linkages within urban settings imply that income growth, rather than

price-induced substitution, is likely the predominant driver of dietary diversification.

These elasticity patterns, which are broadly consistent with recent evidence from sub-Saharan Africa, highlight a greater demand responsiveness among lower-expenditure households, particularly for animal-source foods and essential staples. Such findings underscore the potential utility of carefully designed price- and income-targeted welfare policies to enhance food security and nutritional outcomes.

3.4.2 Diet costs and quality

Least-cost diets are more expensive in rural than urban areas on average. The least-expensive combination of foods in rural areas is 2.61 PPP, compared to 2.52 PPP in urban areas (table 3.5). Average national non-food poverty lines are much lower than the average CoHD, ranging from 0.81 PPP in Niger to 2.02 PPP in Senegal.

Table 3.5: Cost and affordability of a healthy diet

	CoHD	Non-food poverty line	Cons. exp.	% that cannot afford	Affordability gap
Urban	2.52	1.51	5.46	40.35	1.44
	(0.71)	(0.35)	(3.56)		(3.60)
Rural	2.61	1.42	3.84	61.26	-0.19
	(1.03)	(0.36)	(2.55)		(2.86)
Total	2.57	1.46	4.52	52.54	0.49
	(0.91)	(0.35)	(3.12)		(3.29)

Note: All values are in 2021 PPP. Affordability gap = total consumption expenditure per adult equivalent minus basic needs. Household survey weights applied. Pooled sample for 2018 and 2021.

A significantly larger share of the rural population (61%) cannot afford even the least expensive healthy diet, compared to 40% of the urban population across countries.

The affordability gap is below zero in rural areas, indicating that households cannot meet their basic healthy diet and non-food needs at current income levels. In urban areas, households have more income than is needed to meet their basic needs. On average, urban households have 1.44 PPP/adult/day above what is needed, while rural households need an additional 0.19 PPP/person/day to purchase the least-expensive healthy diet and meet their non-food needs.

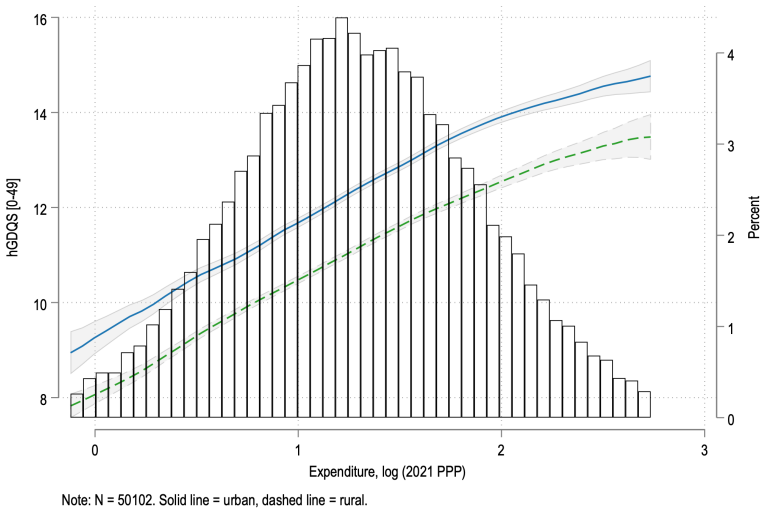
Table 3.6: Unaffordability and consumption of healthy diets, by income quartile

	Cannot afford (0/1)		hGDQS		MFGA		Consumed all 6 (0/1)	
	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban
Q1	0.99	1.00	9.40	10.75	0.49	0.53	0.14	0.23
	0.08	0.06	4.42	4.42	0.11	0.11	0.35	0.42
Q2	0.82	0.77	10.68	12.13	0.52	0.56	0.24	0.33
	0.39	0.42	4.51	4.51	0.11	0.10	0.42	0.47
Q3	0.39	0.33	11.54	13.03	0.54	0.59	0.30	0.42
	0.49	0.47	4.59	4.70	0.11	0.11	0.46	0.49
Q4	0.06	0.02	12.53	14.15	0.57	0.62	0.39	0.50
	0.23	0.12	4.93	5.05	0.11	0.12	0.49	0.50
Total	0.61	0.40	10.88	12.92	0.53	0.58	0.25	0.40
	0.49	0.49	4.73	4.90	0.11	0.12	0.44	0.49
Observations	28970	22155	28959	22153	27440	21649	28970	22156

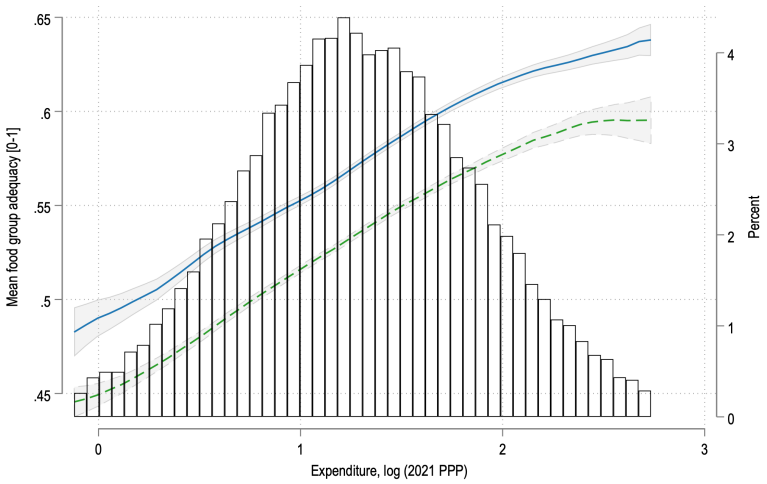
Note: MFGA = mean food group adequacy; hGDQS = household Global Diet Quality Score. Household panel survey weights applied. Pooled sample for 2018 and 2021.

Table 3.6 shows a dissonance between being able to afford a healthy diet and consuming one. While nearly all urban households in the fourth income quartile can afford a healthy diet, just above half of those households (50%) consumed a non-zero quantity of each of the six recommended food groups in the past week. Urban households in higher income quartiles have a mean food group adequacy of 0.59 and 0.62, only slightly higher than that of the poorest urban households (0.53). Rural households are less able to afford healthy diets, less likely to consume all six recommended food groups, and have lower average food group adequacy relative to urban households, regardless of income classification.

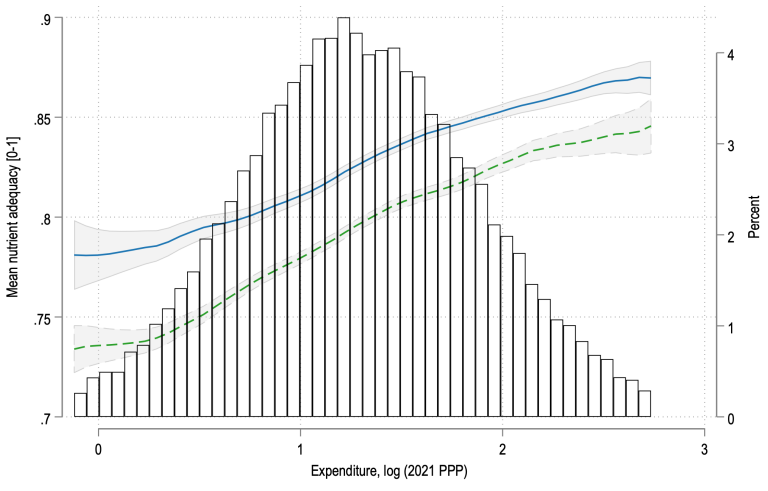
However, figure 3.1 shows that all metrics of diet quality improve linearly with income, at least across the income spectrum observed in the sample. There is no evidence of an inverted-U shape relationship between diet quality and income here.



Note: N = 50102. Solid line = urban, dashed line = rural.



Note: N = 50102. Solid line = urban, dashed line = rural.

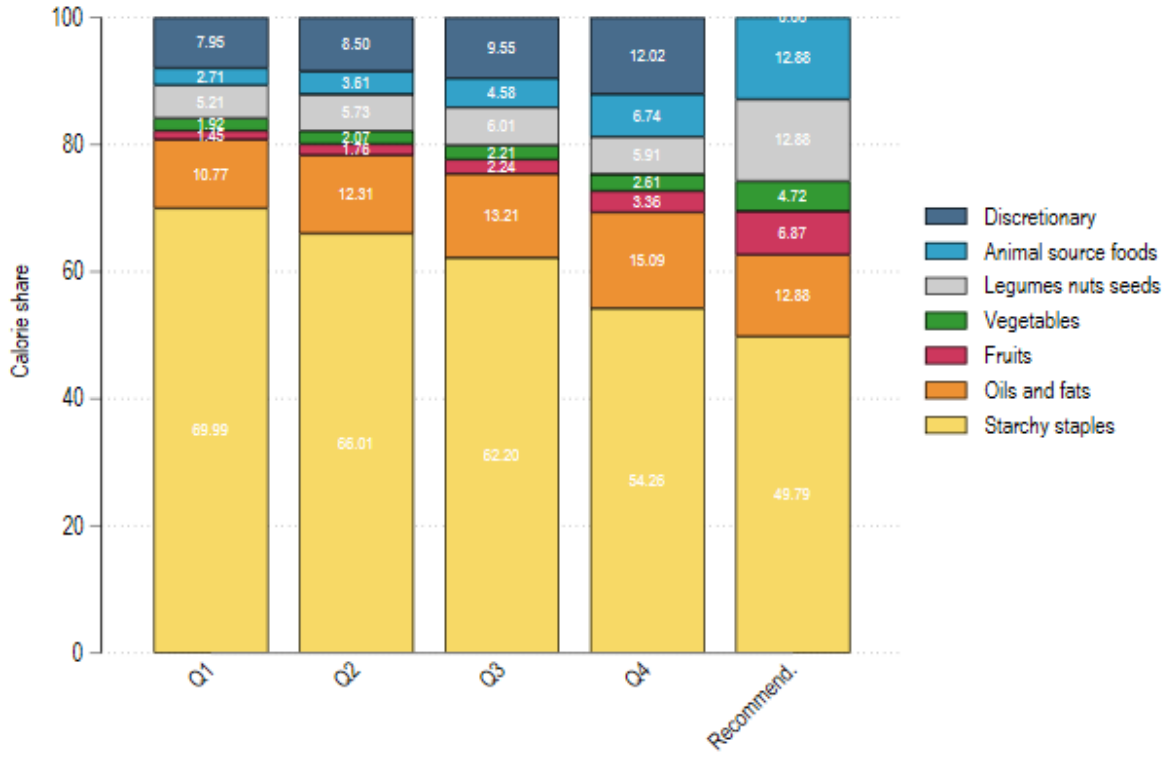


Note: N = 50102. Solid line = urban, dashed line = rural.

Figure 3.1: Diet quality and income

This finding is somewhat surprising given the relatively large share and increasing share of calories allocated to oils and fats and discretionary foods from quartile 1 to quartile 4, and may reflect the composition of the discretionary foods (figure 3.2). While expenditures could be allocated to healthy food groups to improve consumption to recommended levels. Fruits, vegetables, legumes, nuts and seeds, and animal-source foods account for smaller shares of total calories than recommended for all income quartiles. Reducing consumption of starchy staples and reallocating the budget share to healthy food groups would improve diet quality for all income quartiles. Wealthier households should also reduce their consumption of oils and fats.

Figure 3.2: Food group calorie shares in reported diets by income quartile



We supplement Engel curves with "Bennett curves", named after Bennett's Law, to demonstrate how both the budget share and calorie share change as incomes rise. We see in figure 3.3 that starchy staples fall as a share of both expenditure and total calorie intake among wealthier households, as described in Bennett's law, but that even the wealthiest rural household still overconsume starchy staples relative to dietary guidance. In both urban and rural areas, household budget shares for oil and fats stay steady or decline slightly, but calorie shares surpass recommendations among wealthier households. All households, regardless of wealth or locality, underconsume fruits and vegetables. While wealthier households in urban and rural areas make noticeable improvements in fruit consumption, there is very little improvement in vegetable consumption and a large decline in expenditure allocated to veg-

etables as households get wealthier. Households allocate a very small share of their total budget to fruits and vegetables. A similar pattern holds for legumes, nuts and seeds, in sharp contrast to the rising expenditure and calorie share for animal-source foods.

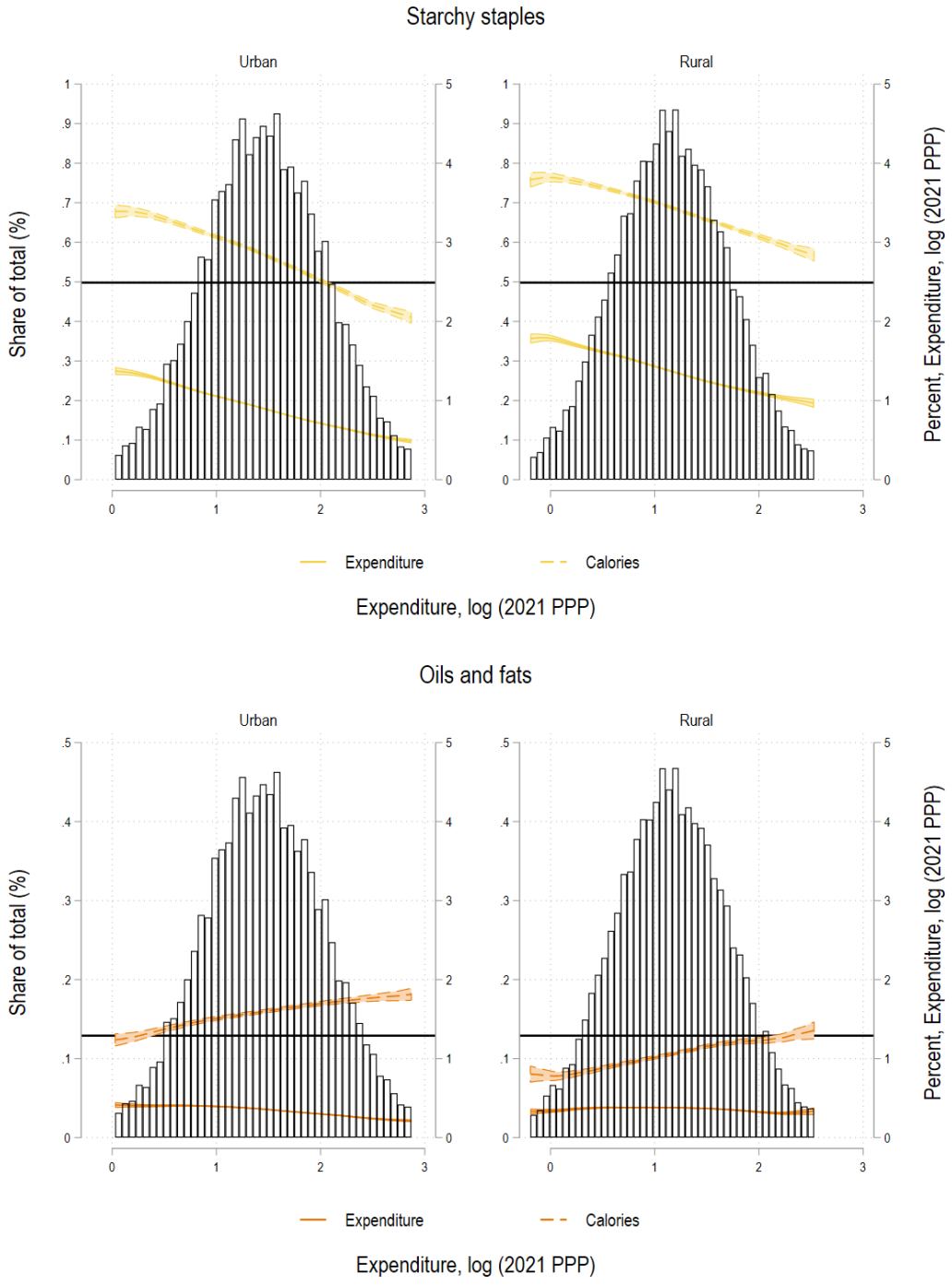


Figure 3.3: Engel and Bennett curves: Rural-urban, pooled sample

Note: Figures are made with lpolyci and show 95% confidence intervals. The solid black line represents the calorie share target defined by the Healthy Diet Basket. Bennett curves are named after Bennett's Law, which states that households consume a small share of calories from energy-dense staples. All figures are local polynomial smooth figures of calories shares and the log of total expenditure per adult equivalent per day in 2021 purchasing power parity (PPP) international dollars. All figures are truncated at the 1st and 99th percentiles of total expenditure. The histogram shows the distribution of the logged total expenditure.

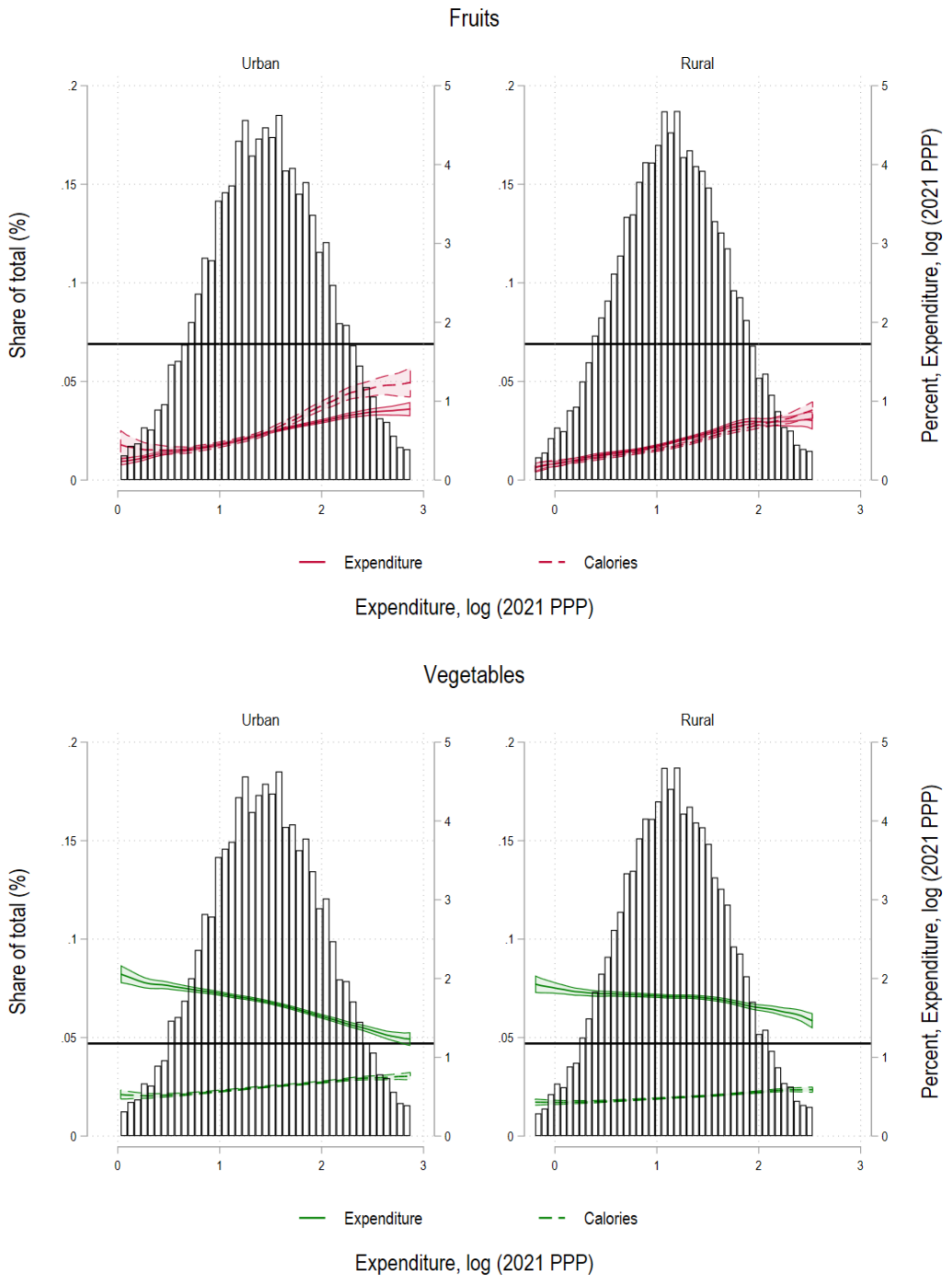


Figure 3.4: Engel and Bennett curves: Rural-urban, pooled sample

Note: Figures are made with lpolyci and show 95% confidence intervals. The solid black line represents the calorie share target defined by the Healthy Diet Basket. Bennett curves are named after Bennett's Law, which states that households consume a small share of calories from energy-dense staples. All figures are local polynomial smooth figures of calories shares and the log of total expenditure per adult equivalent per day in 2021 purchasing power parity (PPP) international dollars. All figures are truncated at the 1st and 99th percentiles of total expenditure. The histogram shows the distribution of the logged total expenditure.

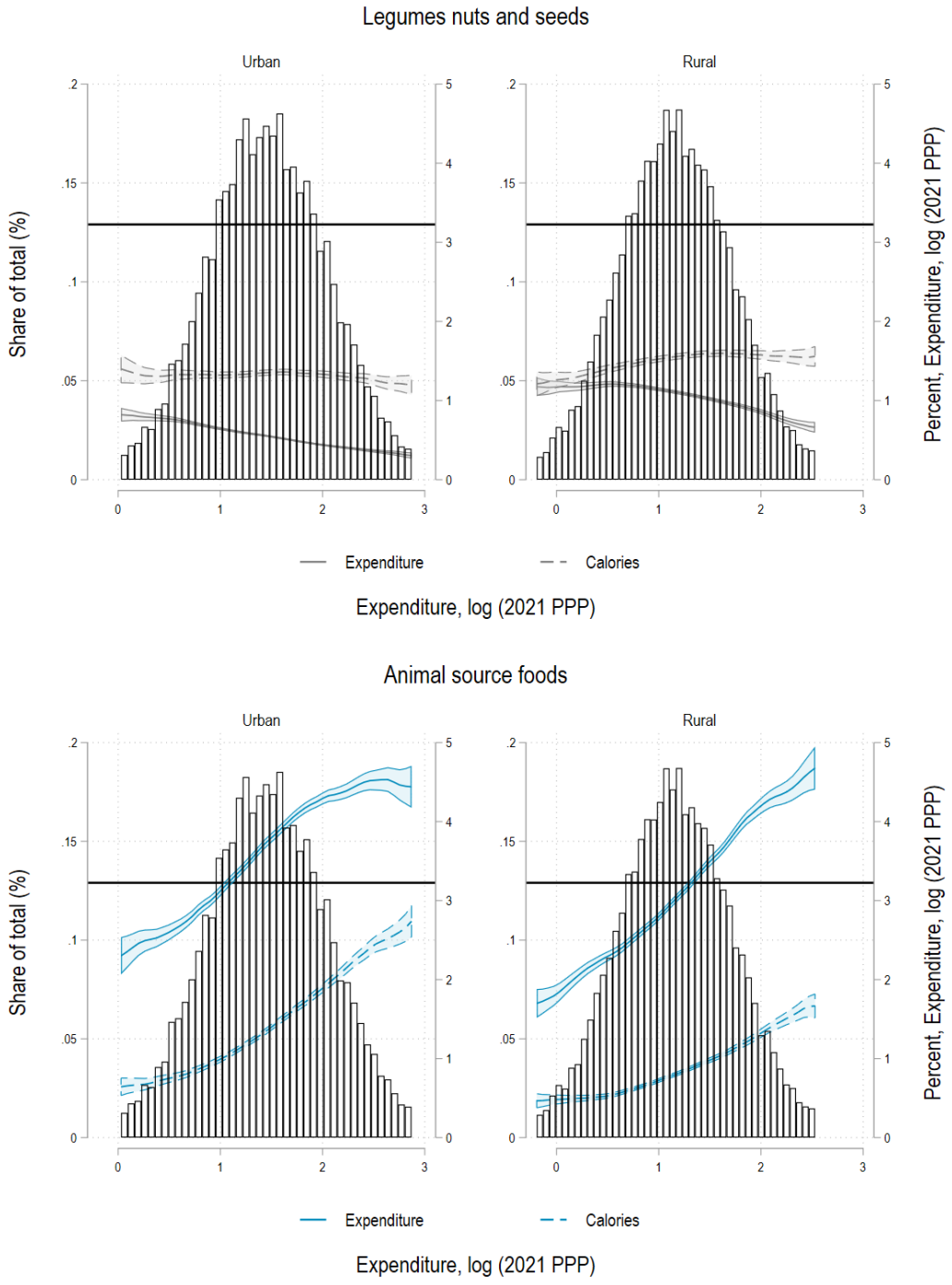


Figure 3.5: Engel and Bennett curves: Rural-urban, pooled sample

Note: Figures are made with lpolyci and show 95% confidence intervals. The solid black line represents the calorie share target defined by the Healthy Diet Basket. Bennett curves are named after Bennett's Law, which states that households consume a small share of calories from energy-dense staples. All figures are local polynomial smooth figures of calories shares and the log of total expenditure per adult equivalent per day in 2021 purchasing power parity (PPP) international dollars. All figures are truncated at the 1st and 99th percentiles of total expenditure. The histogram shows the distribution of the logged total expenditure.

The rising expenditure on animal-source foods does level off at higher income levels, without bringing households up to recommended levels of animal-source food intakes. If households could reallocate budgets towards less-expensive but nutrient-dense animal-source foods (e.g., dried fish), they may achieve recommended consumption levels.

In contrast, discretionary consumption is higher than recommended levels (figure 3.6). Urban and rural households spend a similar share of their budget on discretionary foods, which include items like sugary or savory snacks, as well as condiments and beverages. The large budget share on these items and the high share of calories among wealthier households (10-15% of total calories) suggest that households are unlikely to move to eat healthier as they get wealthier.

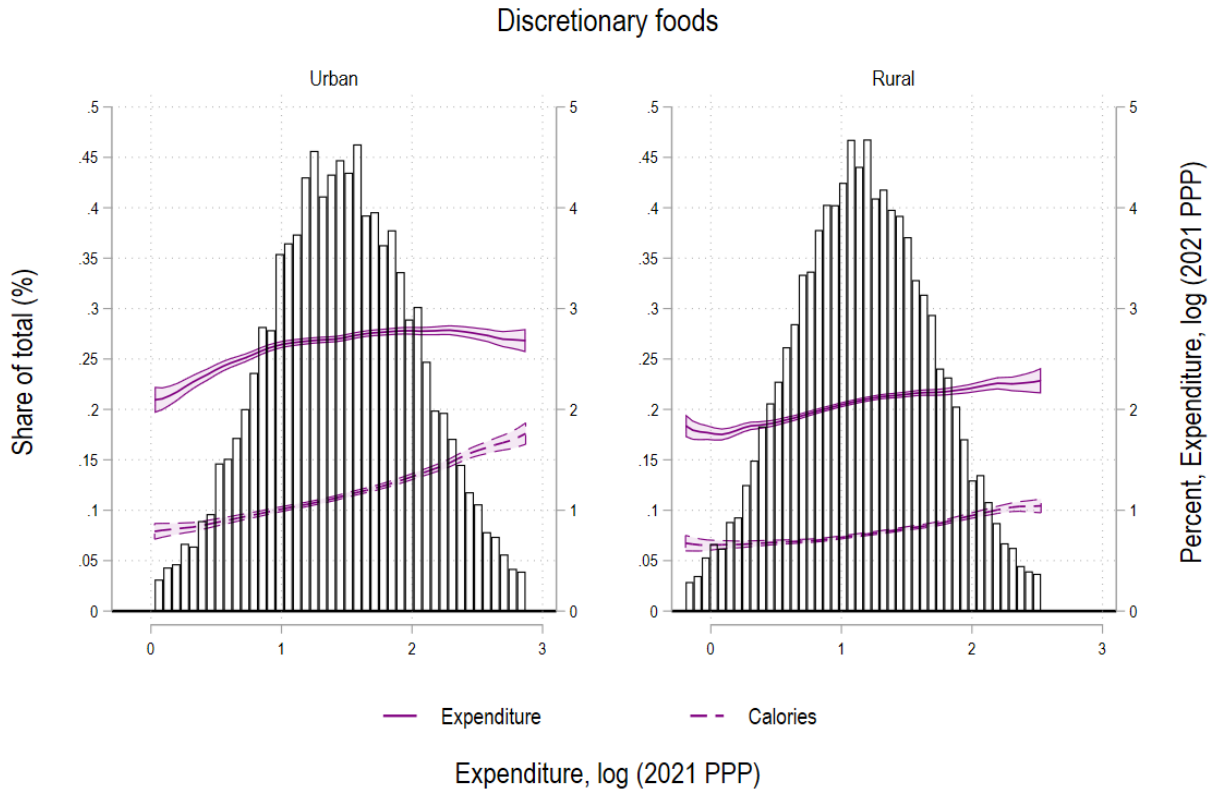
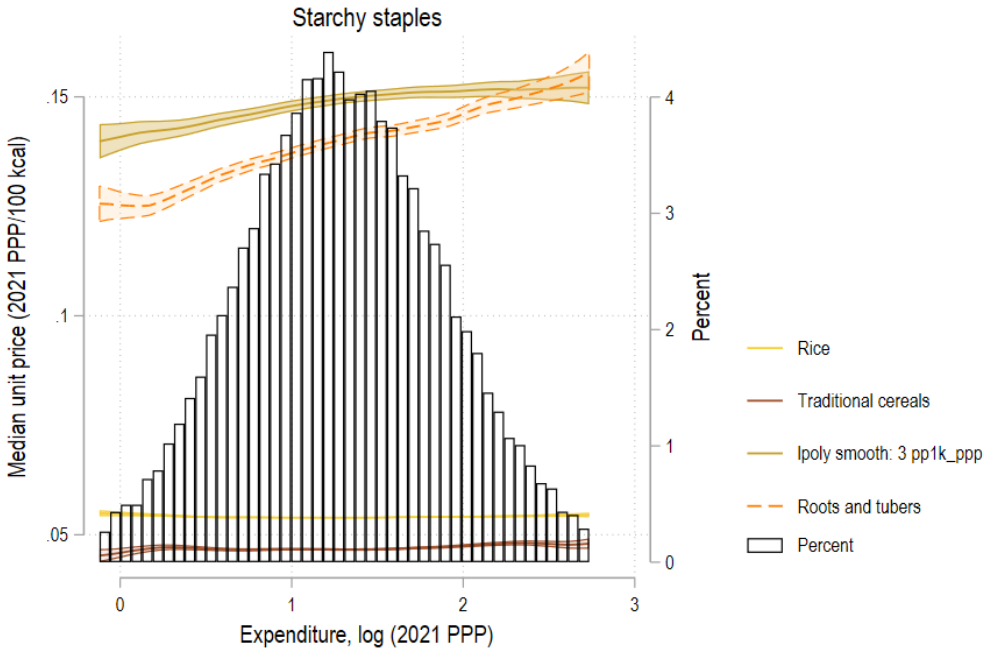


Figure 3.6: Engel and Bennett curves: Rural-urban, pooled sample

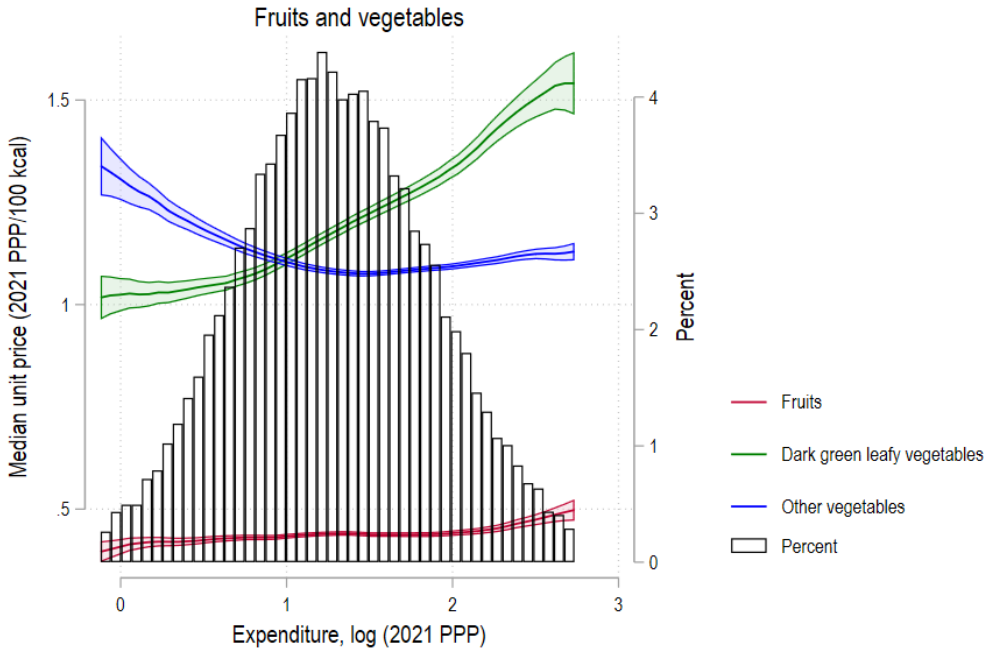
Note: Figures are made with lpolyci and show 95% confidence intervals. The solid black line represents the calorie share target defined by the Healthy Diet Basket. No calories are required from discretionary foods in the HDB. Bennett curves are named after Bennett's Law, which states that households consume a small share of calories from energy-dense staples. All figures are local polynomial smooth figures of calories shares and the log of total expenditure per adult equivalent per day in 2021 purchasing power parity (PPP) international dollars. All figures are truncated at the 1st and 99th percentiles of total expenditure. The histogram shows the distribution of the logged total expenditure.

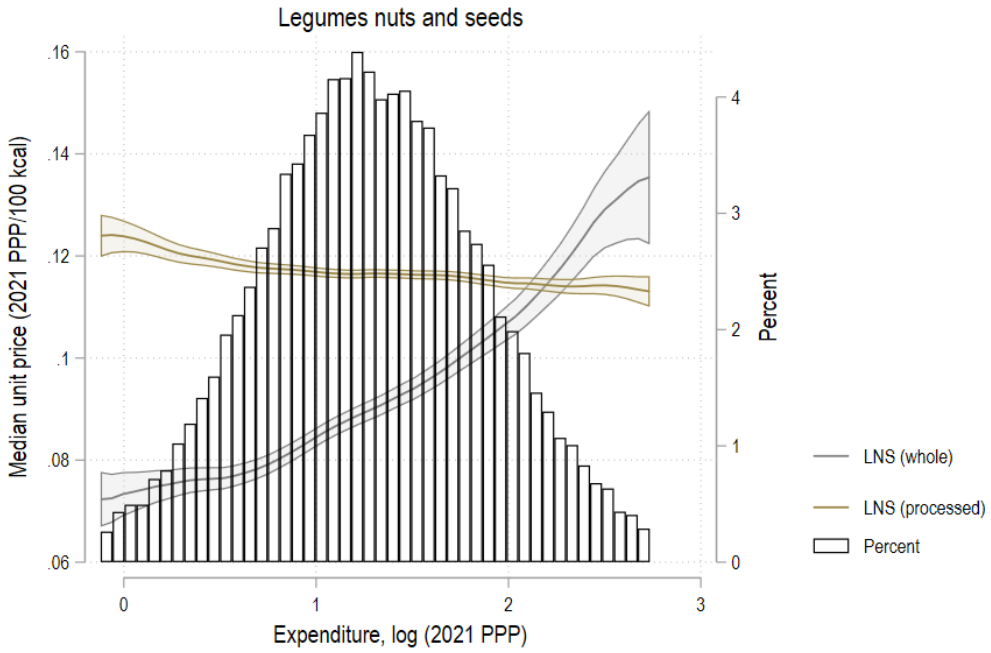
Wealthier households face higher prices or upgrade spending for some food groups, such as roots and tubers, oils and fats, dark green leafy vegetables, whole legumes, nuts and seeds,

and fish.


Starchy staples
Median unit price (2021 PPP/100 kcal)
.15
.1
.05
Percent
4
3
2
1
0
0
1
2
3
Expenditure, log (2021 PPP)
Rice
Traditional cereals
lpoly smooth: 3 pp1k_ppp
Roots and tubers
Percent

Oils and fats
Median unit price (2021 PPP/100 kcal)
.062
.06
.058
.056
.054
Percent
4
3
2
1
0
0
1
2
3
Expenditure, log (2021 PPP)
Oils and fats
Percent


Fruits and vegetables
Median unit price (2021 PPP/100 kcal)
1.5
1
.5
Percent
4
3
2
1
0
0
1
2
3
Expenditure, log (2021 PPP)
Fruits
Dark green leafy vegetables
Other vegetables
Percent


Legumes nuts and seeds
Median unit price (2021 PPP/100 kcal)
.16
.14
.12
.1
.08
.06
Percent
4
3
2
1
0
0
1
2
3
Expenditure, log (2021 PPP)
LNS (whole)
LNS (processed)
Percent

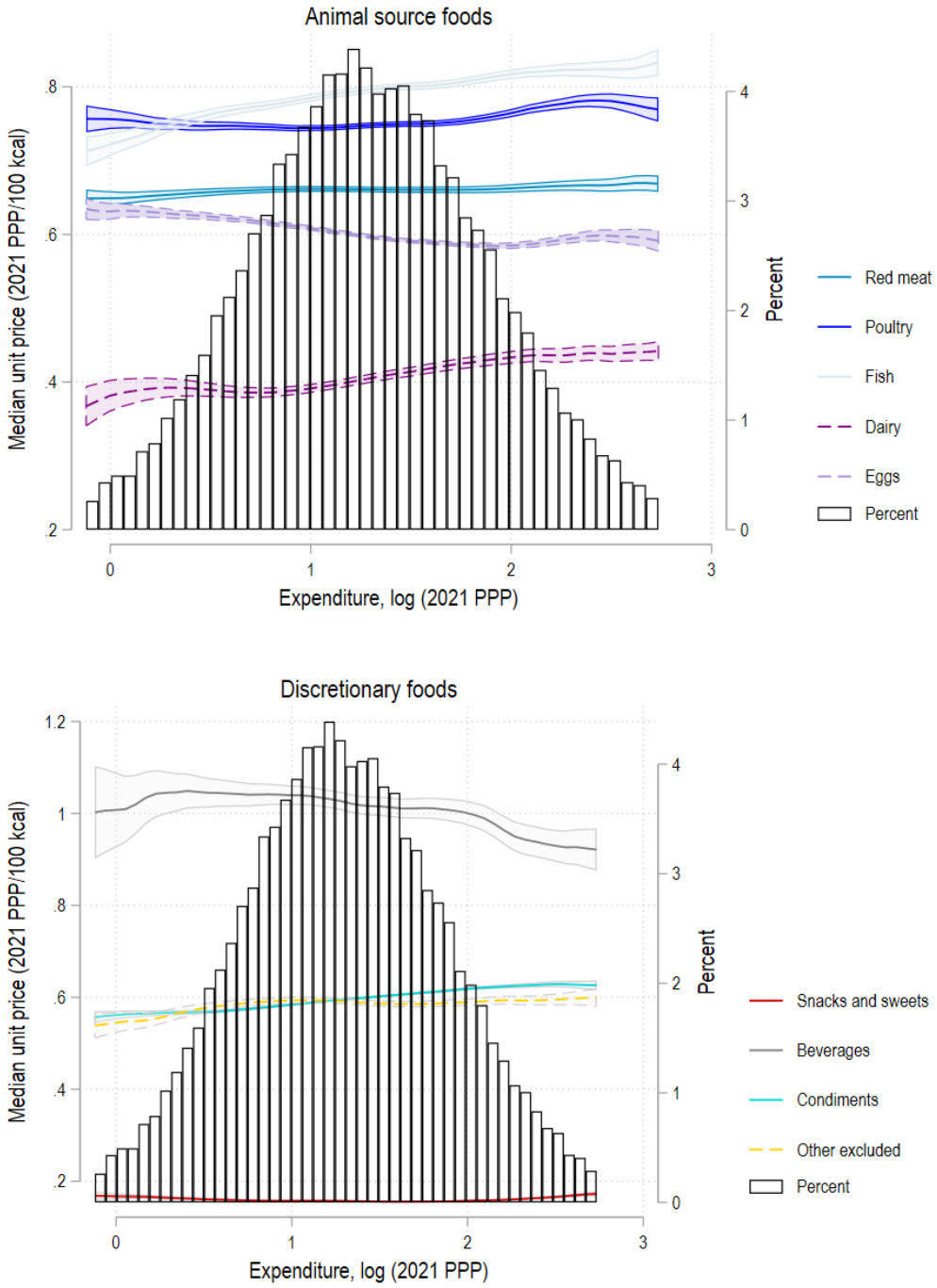


Figure 3.9: Unit prices, pooled sample

Note: Figures are made with lpolyci and show 95% confidence intervals. All figures are local polynomial smooth figures of median unit prices per 1000 kcal and the log of total expenditure per adult equivalent per day in 2021 purchasing power parity (PPP) international dollars. All figures are truncated at the 1st and 99th percentiles of total expenditure. The histogram shows the distribution of the logged total expenditure.

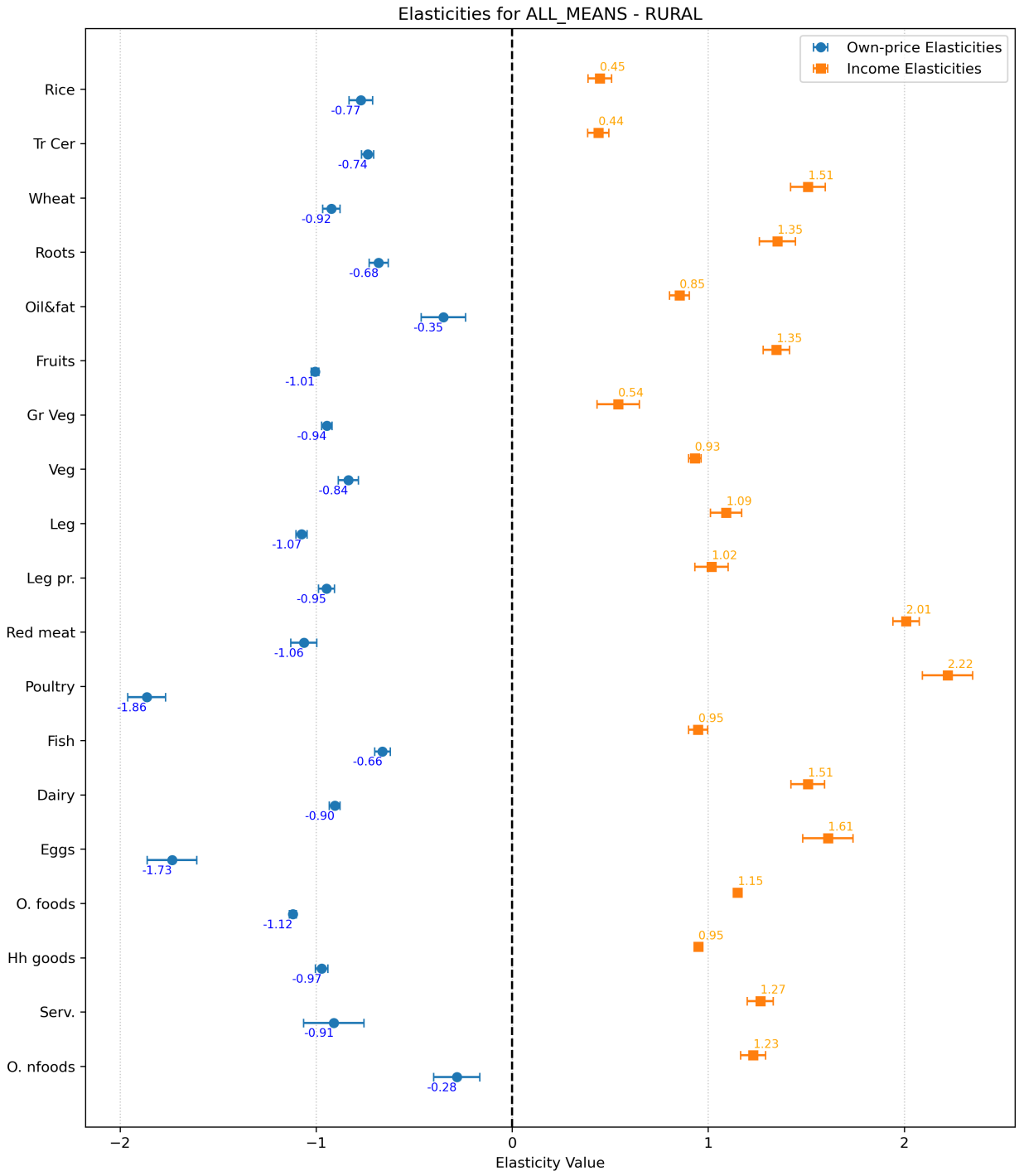
3.4.3 Demand estimates, affordability and diet quality

The demand system estimates in Section 3.4.1 offer essential insights for interpreting the diet quality metrics and affordability gaps presented in Sections 3.4.2 and **??**. A key insight is the disconnect between the affordability of healthy diets and their actual consumption. Although the affordability of healthy diets increases with higher income, this does not result in a proportional improvement in dietary quality. The demand elasticities provide further explanation for these trends by illustrating how households adjust their spending priorities in response to changes in income and prices.

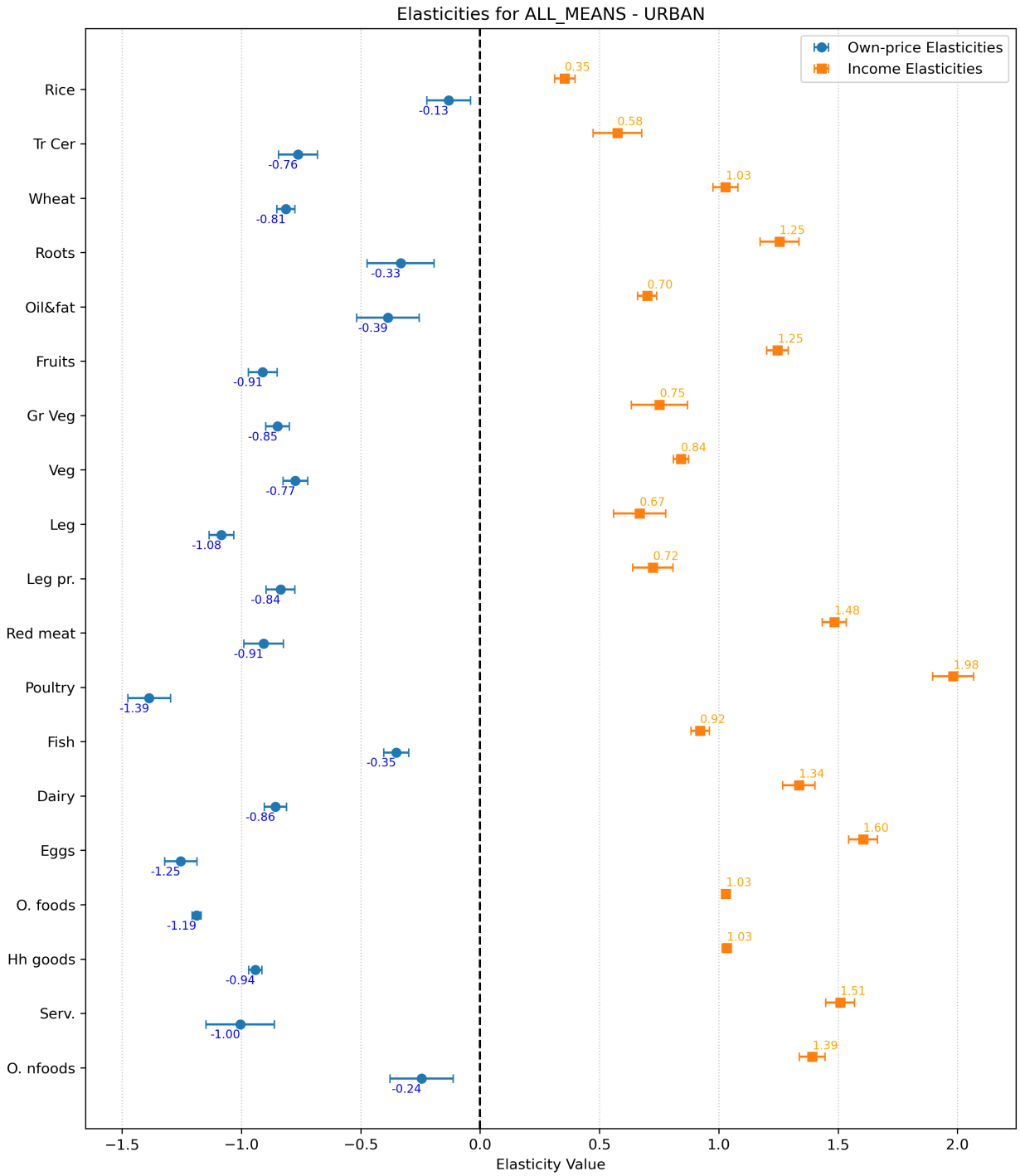
The positive income elasticities observed for every food category indicate that all are normal goods; however, the degree of responsiveness varies significantly across categories. In both rural and urban areas, animal-source foods (red meat, poultry, eggs, dairy) consistently have the highest income elasticities. This indicates that as income increases, households tend to spend a greater portion of their income on these items. While these foods contribute to a healthy diet, this strong preference suggests that income gains might be directed toward more expensive, aspirational foods rather than more affordable, healthy options like legumes or vegetables. This trend provides key insights into the nutritional transition occurring in the region, where diets are shifting away from staples and pulses toward animal proteins as income rises.

In contrast, traditional cereals, rice, and vegetables-—necessities–have income elasticities less than one, implying that their consumption increases less proportionally with rising income. This trend is especially noticeable in urban areas, where “other foods”—which include discretionary items—make up the largest single expenditure category across all income levels. The higher income elasticity for “other foods” and non-food items, compared to many components of a healthy diet, indicates that a significant portion of additional income is likely spent on these non-essential items. As a result, the potential for income growth to enhance diet quality is limited.

Figure 3.10: Income and price elasticities, pooled sample



(a) Rural areas



(b) Urban areas

Price elasticities provide additional insights. In rural households, staple foods like rice, traditional cereals, and wheat are price-inelastic, meaning their consumption remains stable despite price fluctuations. This suggests that these foods are essential and non-negotiable components of the diet. In contrast, poultry and eggs are price elastic, especially among the poorest quartile of the population. This finding is important because it suggests that

price subsidies for these specific nutrient-dense foods could greatly influence consumption, particularly for low-income households.

Interestingly, for low-income households, the absolute value of own-price elasticities for healthy items like green vegetables, other vegetables, and legumes is higher than their income elasticities. This suggests that price-based policies, such as subsidies or targeted vouchers, might be more effective at increasing consumption of these specific healthy foods than general income transfers. The price disparity between urban and rural areas, with fruits being significantly more expensive in rural areas, also highlights a potential area for targeted interventions to improve supply chains for perishable goods.

3.5 Conclusion

This paper investigates the role of income constraints and preferences on the intake of healthy diets in the eight countries in West Africa that are members of the West African Economic and Monetary Union (WAEMU). We specify and estimate a demand system of 19 goods, including 15 food groups that map to the recommended food groups found in the Healthy Diet Basket, a global standard, one group of "other" discretionary foods, and three non-food goods. We complement the price and income elasticity estimates with an analysis of the affordability of healthy diets and actual consumption patterns.

The results reveal a nuanced relationship between income and intake. On one hand, diet quality improves with income. On the other hand, improvements fall short of dietary recommendations in meaningful ways. Even among higher-income households, diets remain out of step with the food-based dietary guidelines, with persistent underconsumption of fruits, vegetables, and legumes, nuts, and seeds. This misalignment is in line with research from other low-and middle-income countries, as well as higher-income settings, that shows that economic access to healthy diets does not guarantee that reallocation of budgets towards healthier choices. Furthermore, an positive association between income and calories from discretionary foods suggests dietary risks.

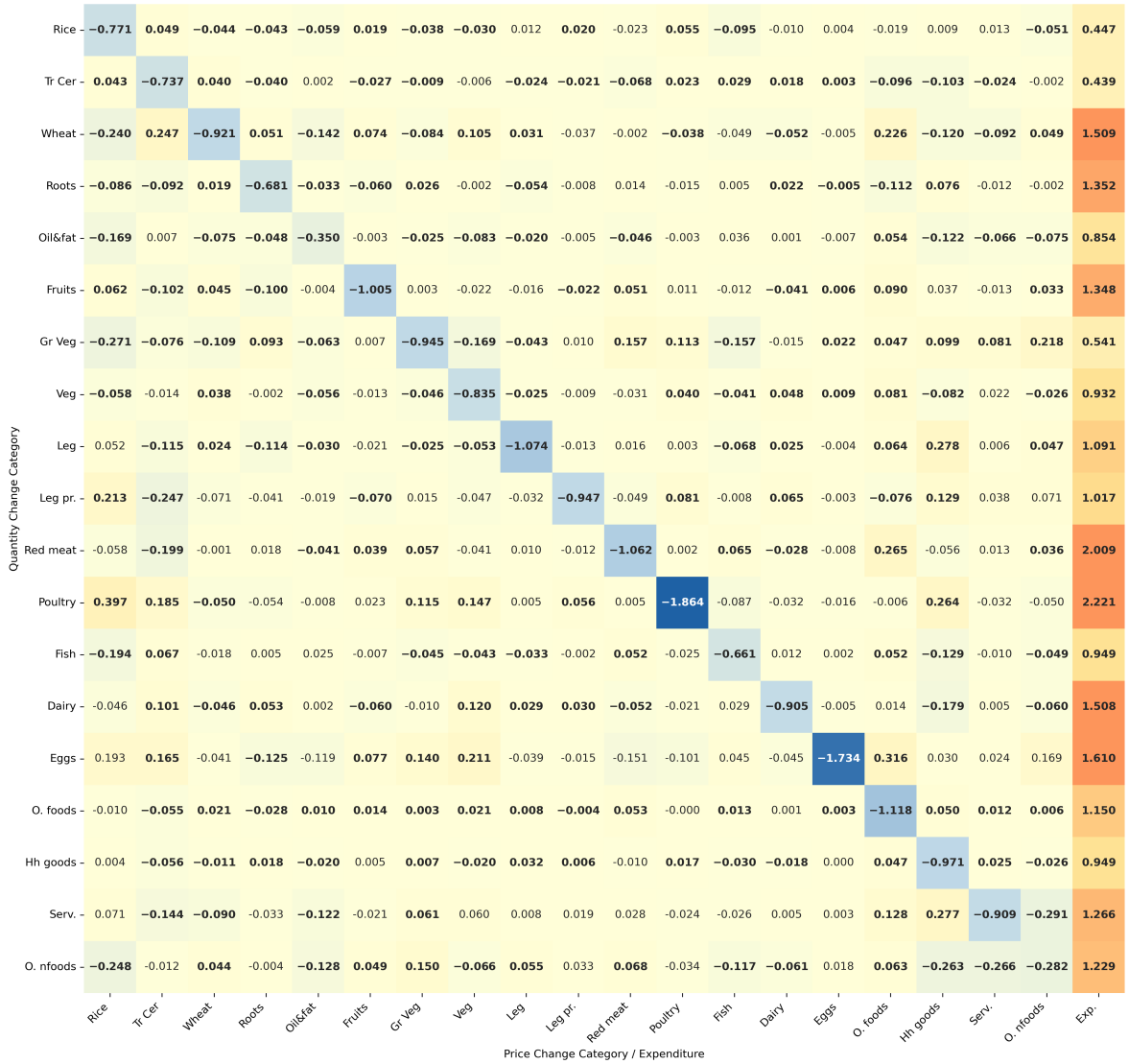
Price and income elasticities support these concerns. Income elasticities are uniformly positive, but they are substantially larger for discretionary foods and non-food goods than for most healthy diet components. Additional income is more likely to be allocated outside the healthy diet basket. At the same time, discretionary foods are relatively price sensitive, suggesting that their consumption could be reduced by modest price changes while vegetables and legumes display higher price than income responsiveness for lower-income households. Price-based interventions like subsidies or vouchers could be effective in promoting their consumption. For less sensitive income or food groups, information or behavioral nudges could be used to shift consumers towards healthier options.

In this context, in-kind transfers of food items that are consumed in small quantities relative to recommendations, such as fruits and vegetables, could be more effective at promoting healthy diets among vulnerable populations if resales are kept at a minimum. Arguably, direct access to healthy foods would ensure that these items are consumed rather than substituted away for less nutritious alternatives. Alternatively, food vouchers explicitly tied to purchasing

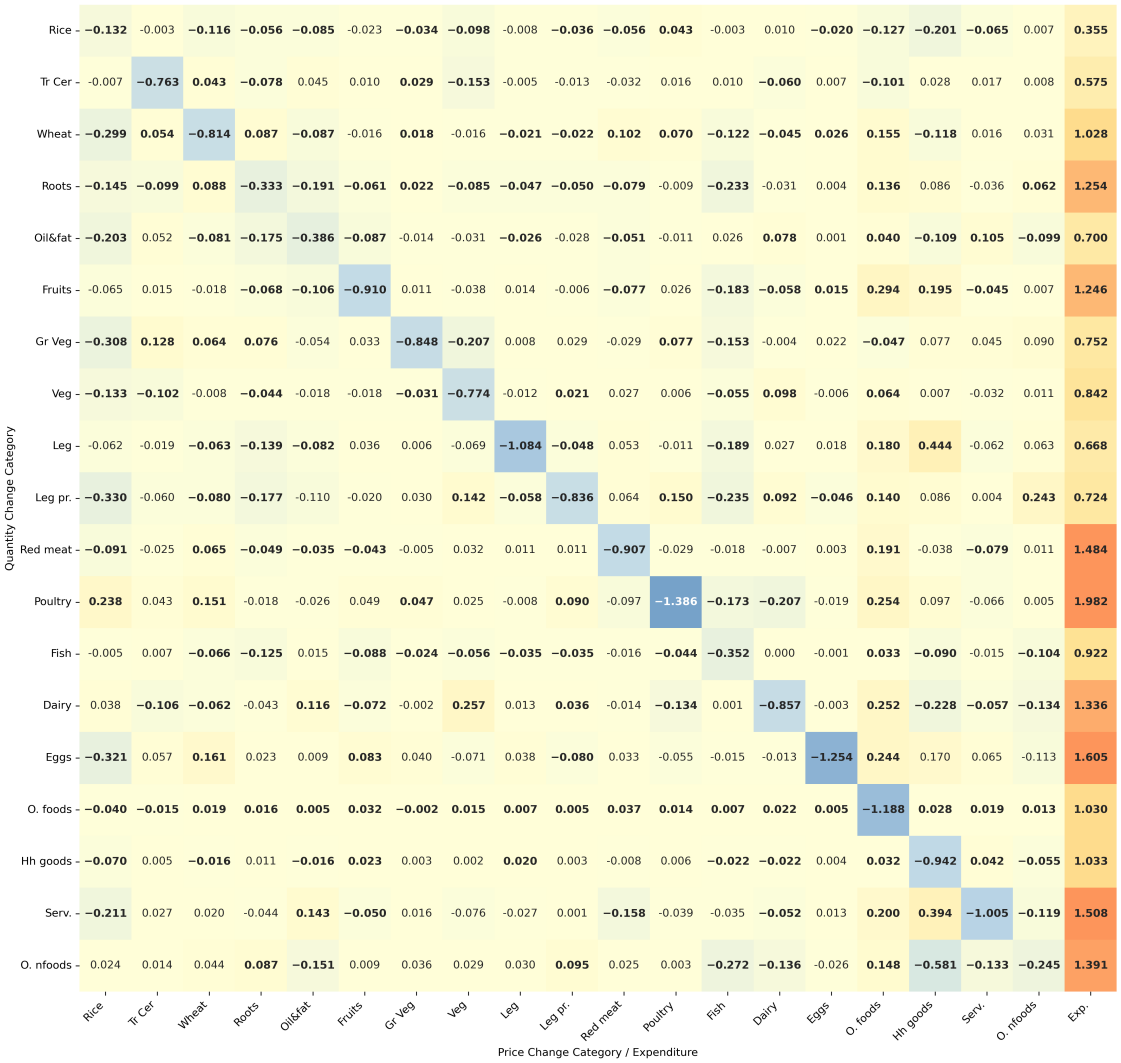
healthy foods represent a promising approach. Such vouchers allow households to select from a range of nutritious options while ensuring that the funds are used exclusively for dietary improvement, especially for low-income households. However, the logistics for implementing these types of policies may be challenging, given the state of physical and administrative infrastructure in these countries.

The evidence from WAEMU countries underscores both the opportunities and limitations of income growth as a pathway to better nutrition. Diet quality does rise with income, but the gap with dietary recommendations persists across the distribution, shaped by patterns of overconsumption of staples and discretionary foods and persistent underconsumption of nutrient-dense items. Addressing these gaps will require a multifaceted policy approach that combines affordability improvements with targeted transfers and and demand-side interventions to shift preferences and behaviors.

Figure 3.11: Price and Income Elasticities

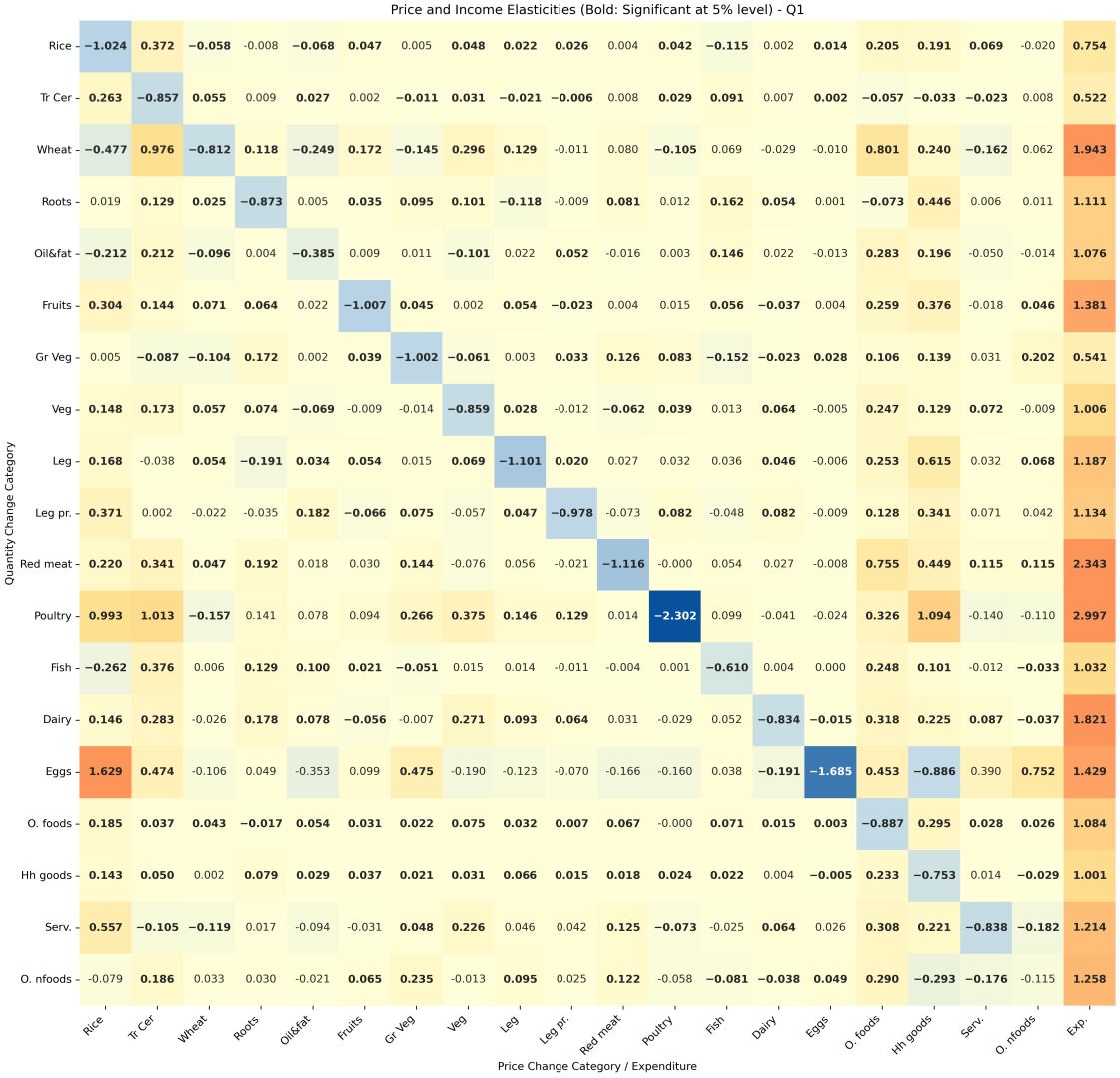


(a) Rural areas

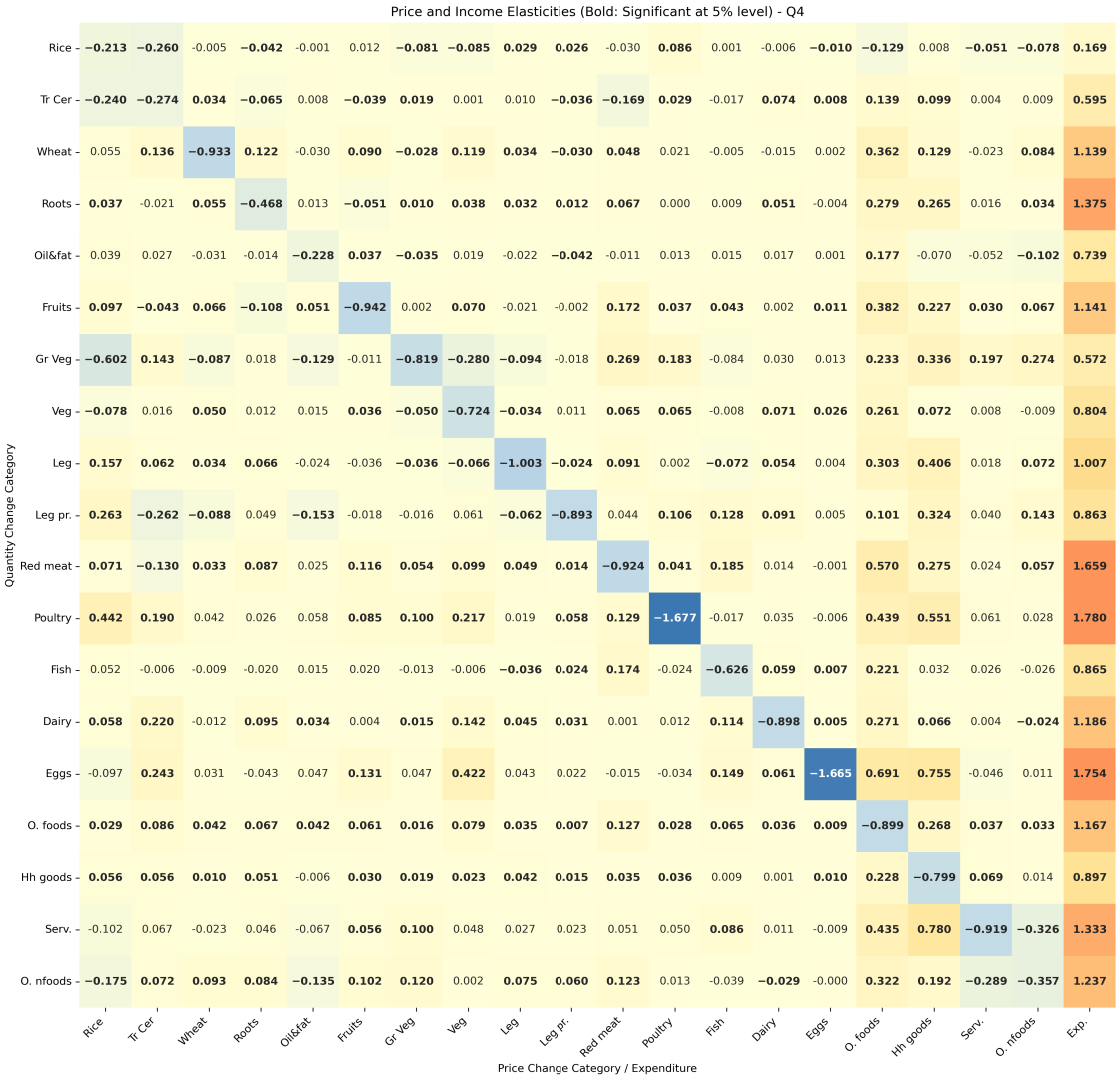


(b) Urban areas

Figure 3.12: Compensated Price and Income Elasticities, Rural

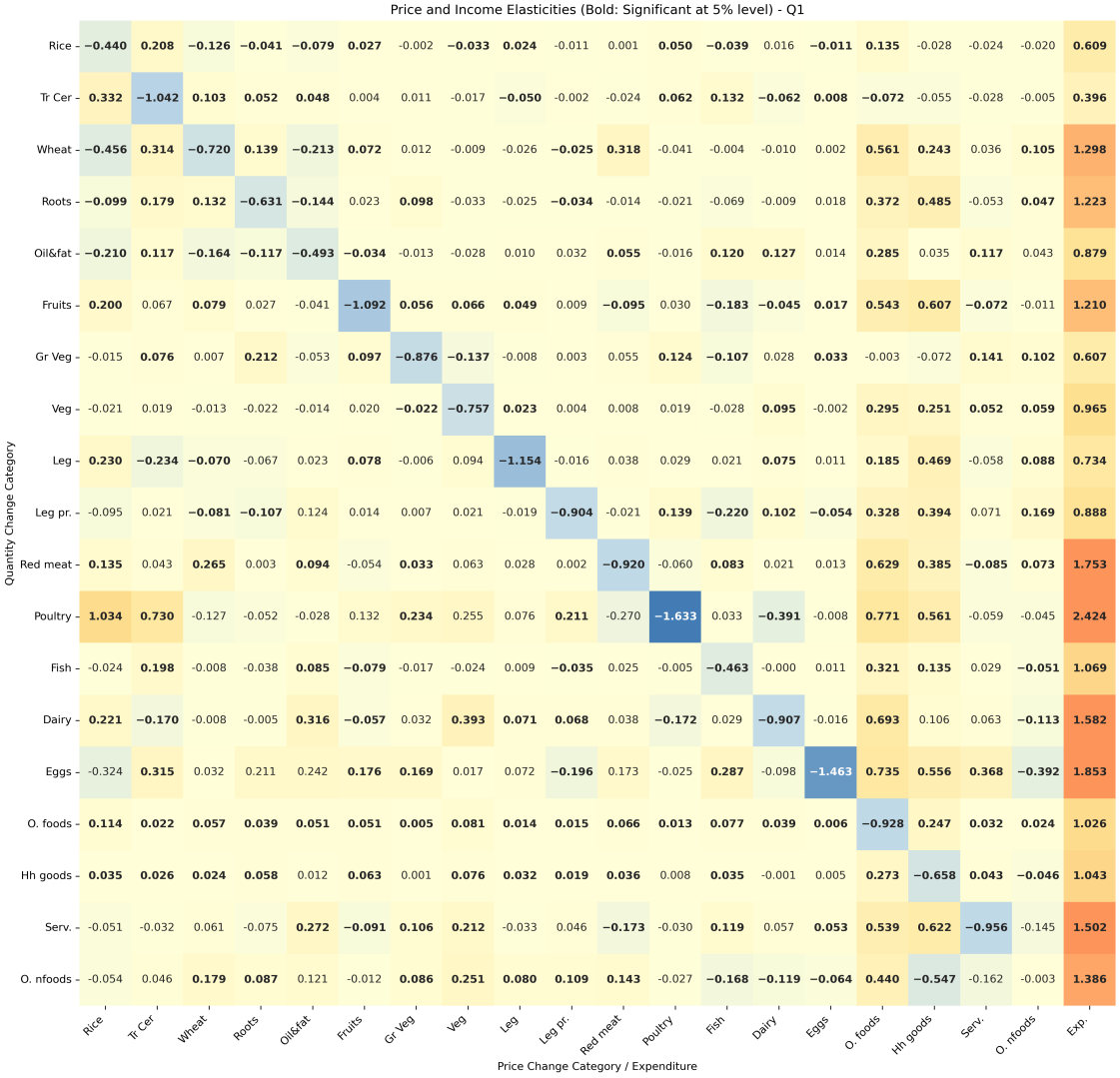


(a) Expenditure Quartile Q1

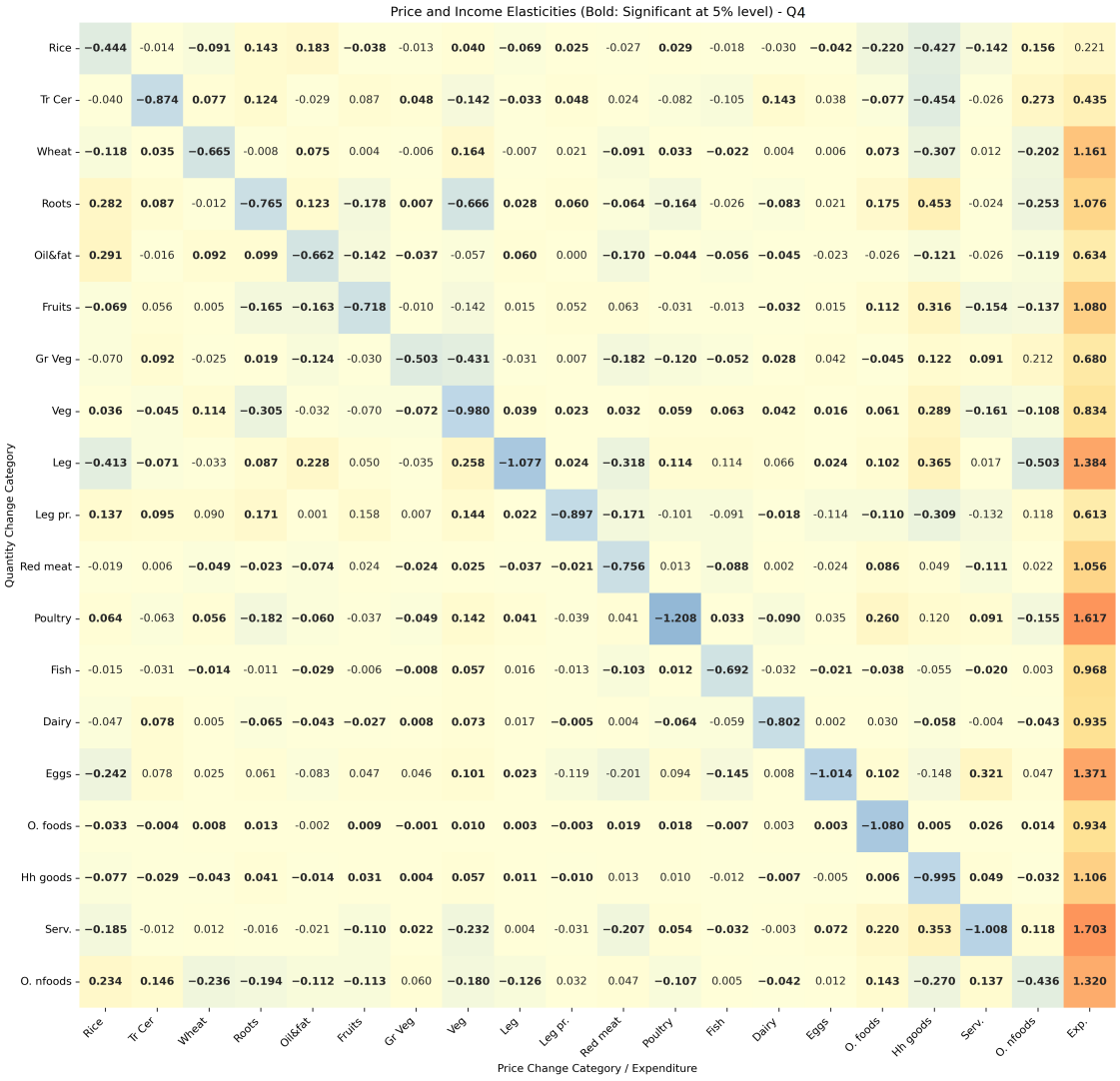


(b) Expenditure Quartile Q4

Figure 3.13: Compensated Price and Income Elasticities, Urban



(a) Expenditure Quartile Q1



(b) Expenditure Quartile Q4

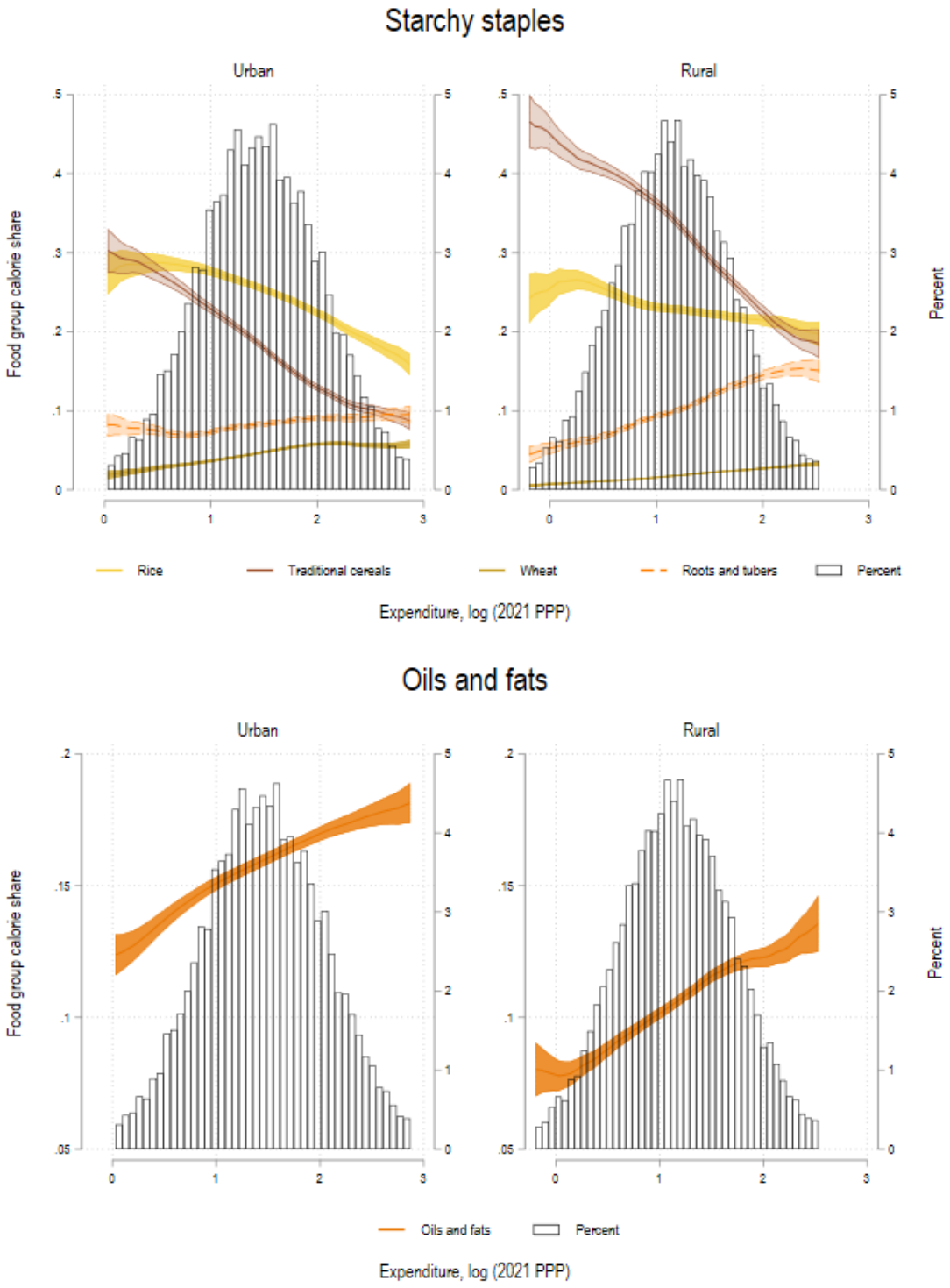


Figure 3.14: Bennett curves: Rural-urban, pooled sample

Note: Bennett curves are named after Bennett's Law, which states that households consume a small share of calories from energy-dense staples. All figures are local polynomial smooth figures of calories shares and the log of total expenditure per adult equivalent per day in 2021 purchasing power parity (PPP) international dollars. All figures are truncated at the 1st and 99th percentiles of total expenditure. The histogram shows the expenditure distribution.

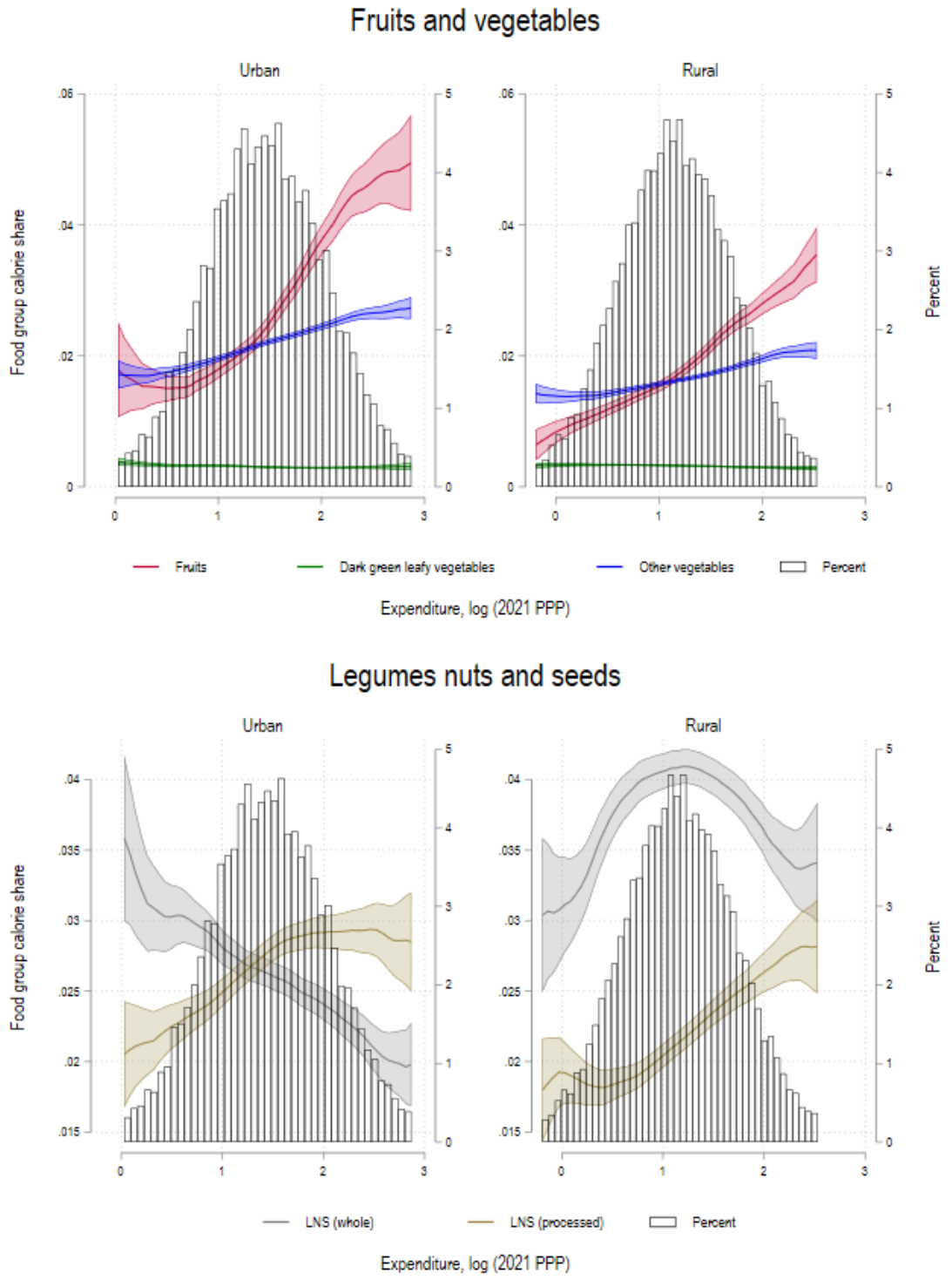


Figure 3.15: Bennett curves: Rural-urban, pooled sample

Note: Bennett curves are named after Bennett's Law, which states that households consume a small share of calories from energy-dense staples. All figures are local polynomial smooth figures of calories shares and the log of total expenditure per adult equivalent per day in 2021 purchasing power parity (PPP) international dollars. All figures are truncated at the 1st and 99th percentiles of total expenditure. The histogram shows the expenditure distribution.

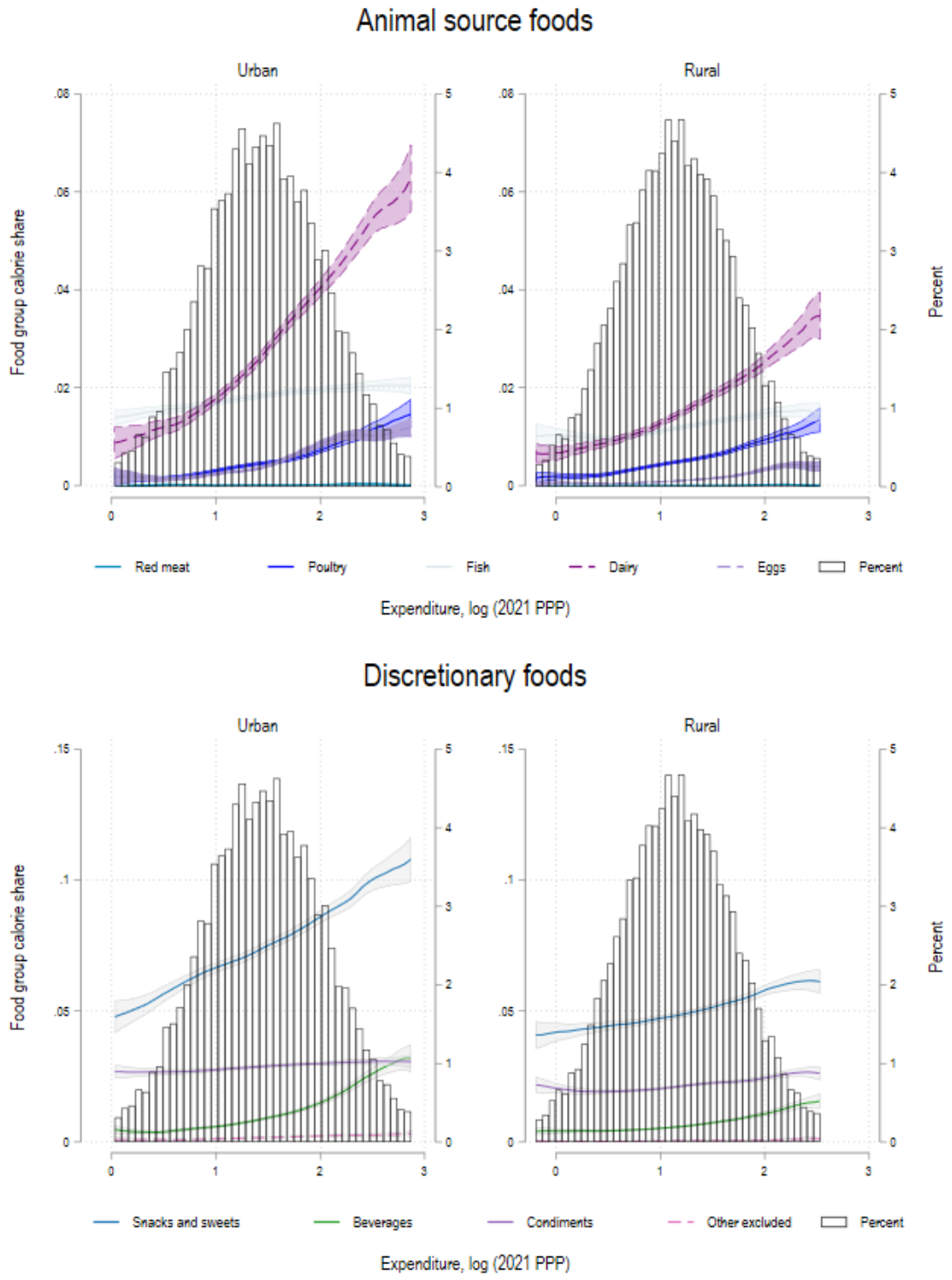


Figure 3.16: Bennett curves: Rural-urban, pooled sample

Note: Bennett curves are named after Bennett's Law, which states that households consume a small share of calories from energy-dense staples. All figures are local polynomial smooth figures of calories shares and the log of total expenditure per adult equivalent per day in 2021 purchasing power parity (PPP) international dollars. All figures are truncated at the 1st and 99th percentiles of total expenditure. The histogram shows the expenditure distribution.

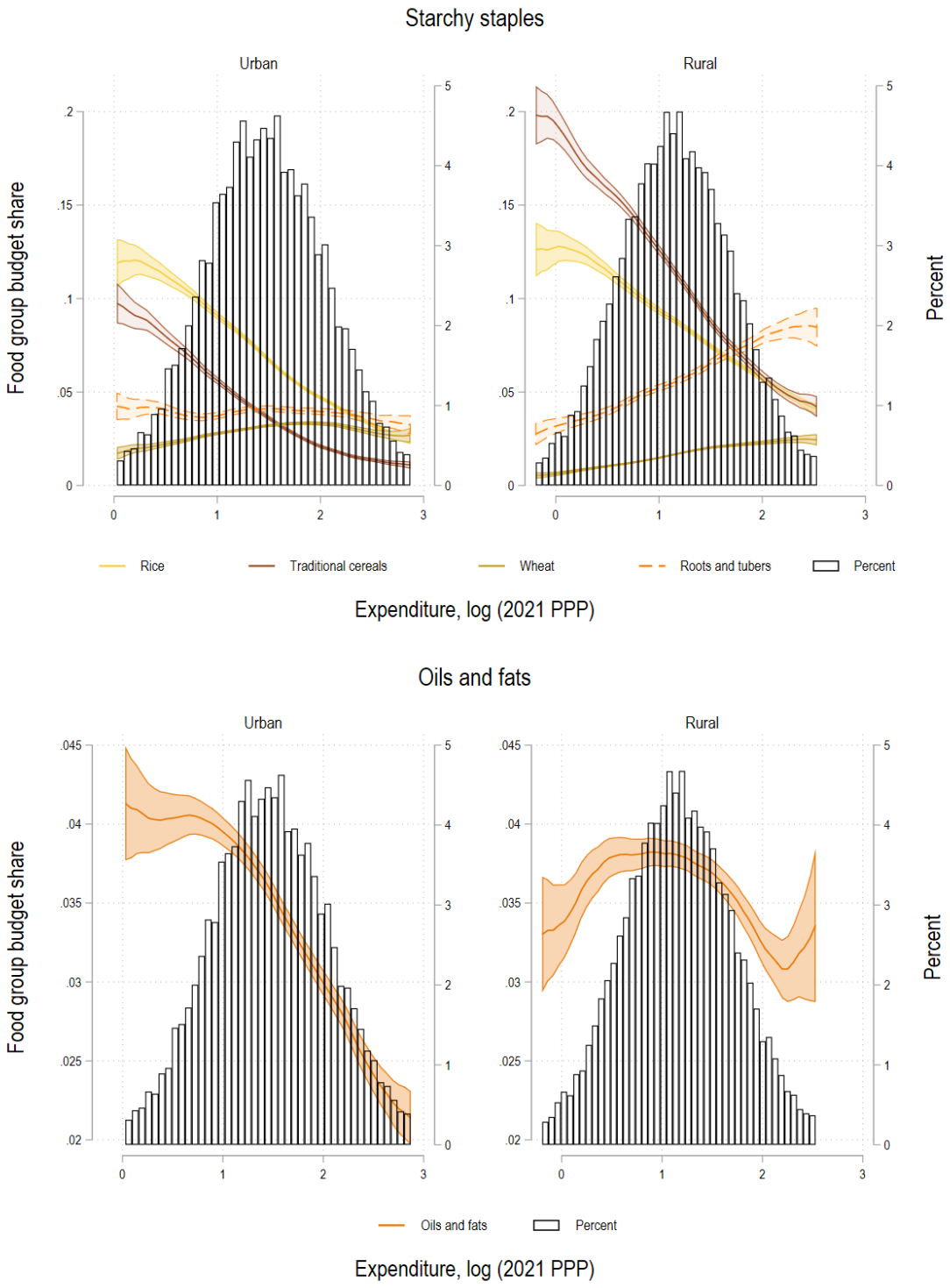


Figure 3.17: Engel curves: Rural-urban, pooled sample

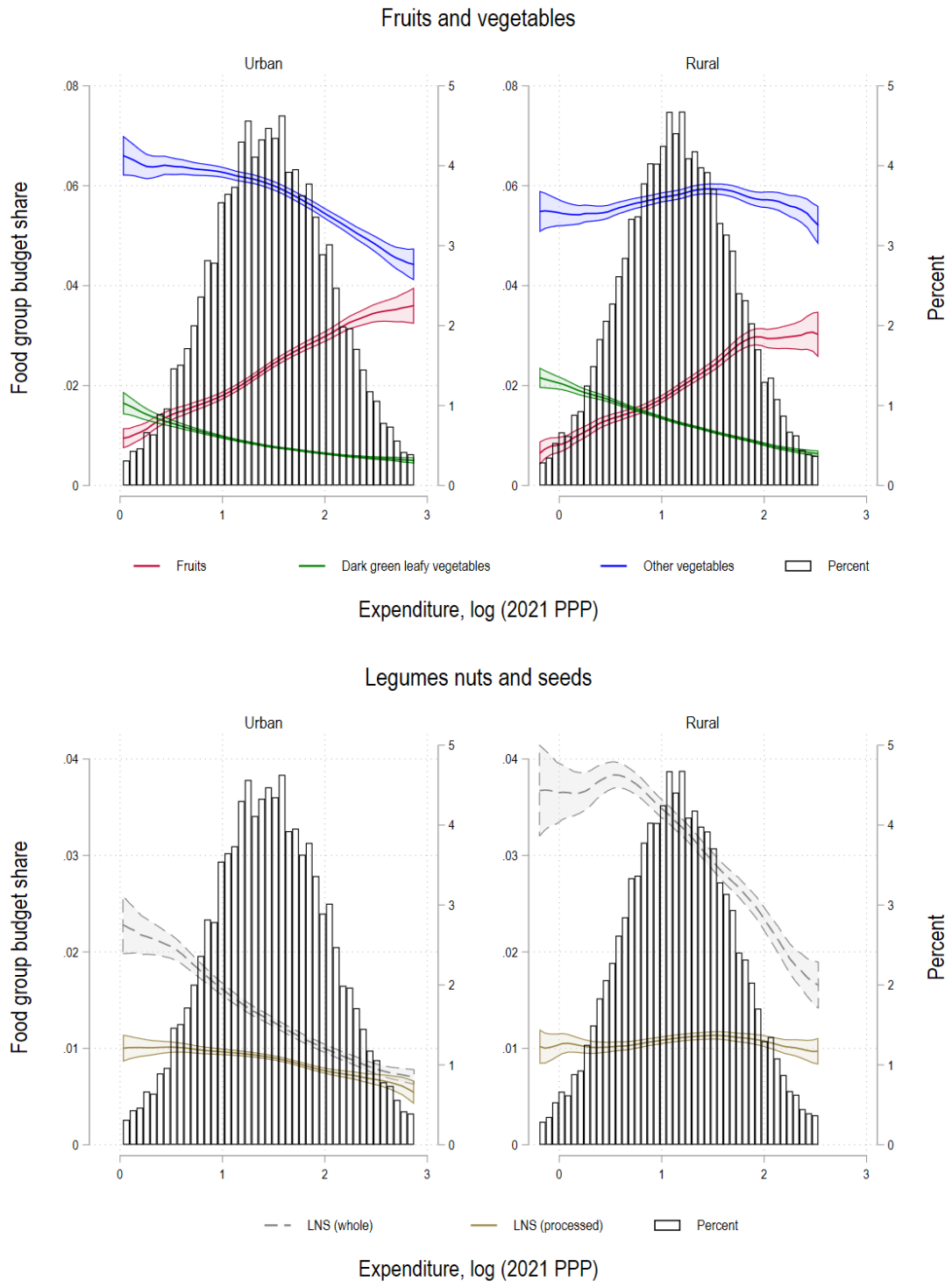


Figure 3.18: Engel curves: Rural-urban, pooled sample

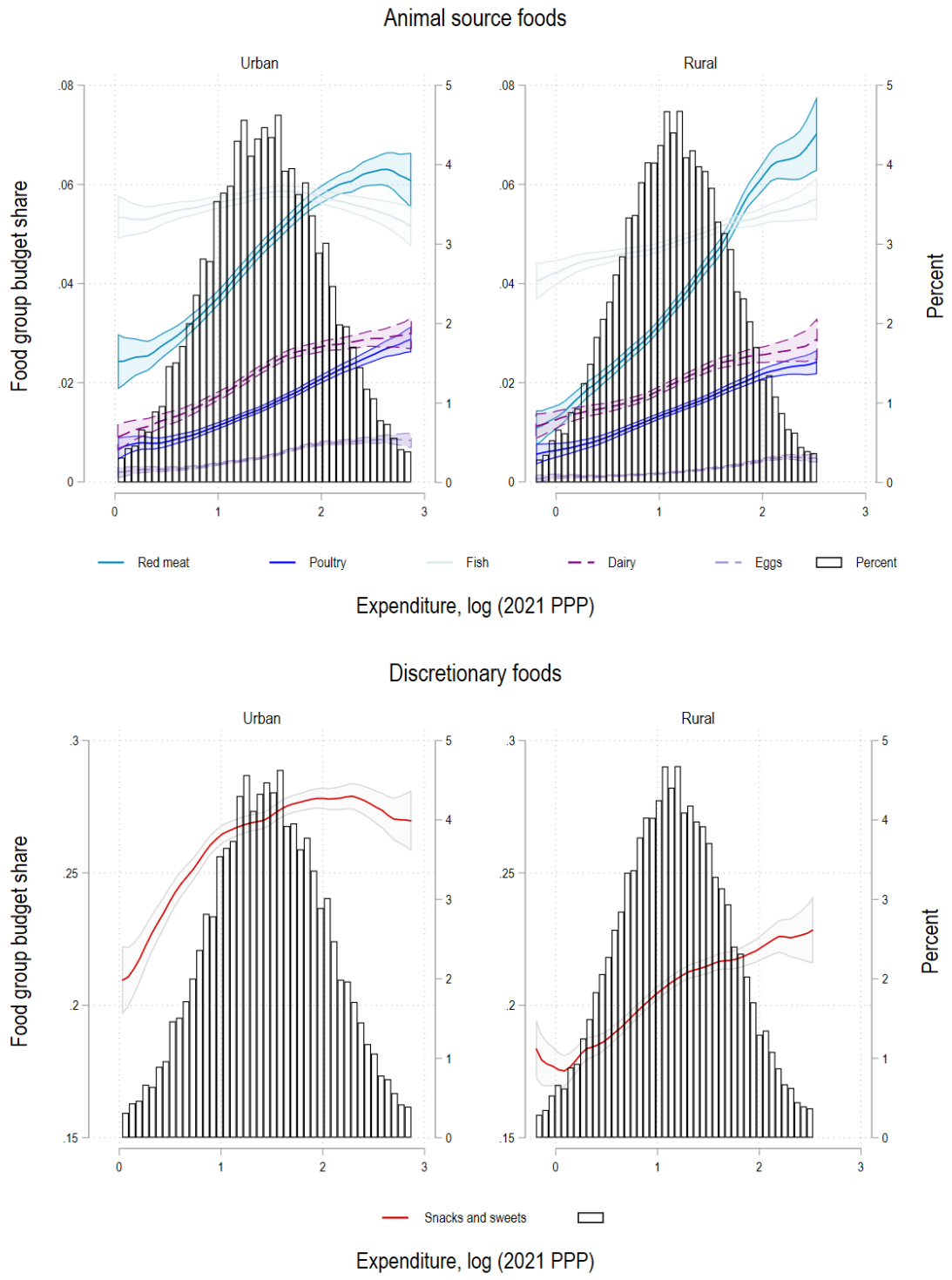


Figure 3.19: Engel curves: Rural-urban, pooled sample

Chapter 4

Fueling diet quality: the cost of cooking healthy diets in Malawi

Abstract

Healthy diets are out of reach for many low-income households in Malawi, and the cost of cooking fuel to prepare diverse foods can shape food choices as food and fuel prices fluctuate. Using nationally representative household and market survey data from 2019–2020, this study estimates a lower bound on the cost of cooking foods consumed and those included in a least-cost healthy diet. Theoretical cooking costs are modeled using food composition data, specific heat capacity, required water, local temperatures and altitudes, and the calorific values and prices of common cooking fuels. I find that cooking energy requirements per calorie are significantly higher for vegetables, starchy staples, and legumes, nuts, and seeds—consistent with their high moisture content and longer cooking times. Fuel prices and stove efficiency result in substantial variation in cooking costs across fuel types, with electricity being the least costly and liquefied petroleum gas (LPG) the most expensive. While cooking costs represent a modest share of total diet costs, they are non-negligible and can alter the composition of least-cost diets, particularly if firewood is the primary fuel source. Incorporating fuel costs in least-cost diets leads to substitution toward foods assumed to be prepared with less time or water-intensive cooking methods, or pre-cooked vendor or prepared foods, such as boiled eggs, dairy, and bread. These findings underscore the importance of considering fuel access and cooking costs in diet affordability assessments and policies to promote healthier diets. Efficient fuels and stoves, low-moisture foods and less water-intensive cooking methods have a considerable impact on cooking fuel requirements.

JEL-Classification: Q18, D12, Q41, O1
Keywords: diet quality, fuel use, development.

4.1 Introduction

Household food choices depend on many factors, including price and the time, fuel, and effort required to prepare meals. While the cost of food is central to research on diets and food security, the cost of cooking food remains understudied, particularly in low-income settings where fuel choices are limited and fuel prices are volatile. Understanding these meal preparation costs is essential to improving access to healthy diets, especially for the nearly 3 billion people worldwide who cannot afford even the least-cost combination of foods needed for health, let alone the fuel to cook them (FAO; IFAD; UNICEF; WFP; WHO, 2024a).

A growing literature has documented how fuel access and cooking costs shape diets. Studies from Malawi, India, Kenya, and South Africa have shown that fuel shortages and rising cooking costs can reduce caloric intake, shift households toward less energy-intensive foods, or limit the number of meals cooked per day (Brouwer et al., 1997; Basole and Basu, 2015; Hunter-Adams et al., 2019; Waswa et al.). In some cases, improved cookstoves or clean energy access have enabled more diverse diets (Anderman et al., 2015), while in others, cooking practices tied to cultural preferences persist (Cundale et al., 2017; Asada).

Despite this evidence, little is known about how cooking fuel costs affect the consumption of healthy diets specifically. In a recent field experiment in Zambia, households receiving solar cookstoves did not have significantly higher nutritional diversity or prepare a larger number dishes per meal. Households reduced the amount of time and money spent on cooking fuel, suggesting this is a priority for households while not the main barrier to healthier diets (McCann et al., 2024). Most studies of cooking costs focus on staple foods or typical meals, without estimating how the cost of cooking varies across diverse food groups recommended for health. Nor do existing methods consistently estimate the fuel or time required to prepare different foods from retail markets. While studies have estimated the energy needs for cooking particular foods or meals (Carlsson-Kanyama; MECS; Kajumba et al., 2022), there is limited evidence linking these estimates to real-world food prices and diets in low-income countries.

This study addresses this gap by estimating the cost of cooking healthy diets in Malawi. I combine retail food and fuel prices with household consumption data to estimate how fuel requirements — key component of meal preparation costs — vary across food groups. Specifically, I test whether the cost to cook a calorie is higher for starchy staples and legumes, nuts, and seeds relative to other food groups recommended in the HDB. Understanding these costs is critical to identifying both constraints and opportunities to improve diets, including the potential for low-cost processed foods to reduce fuel needs while maintaining or improving nutritional quality (Masters et al., 2021).

4.2 Estimates of the cost of cooking

Most research on cooking fuel costs has focused on a small number of foods or typical meals, often in experimental or engineering settings rather than real-world markets. Carlsson-Kanyama estimate the electricity required to cook portions of grains, tubers, and pasta in Sweden, demonstrating the importance of batch cooking and efficient boiling methods. In

East Africa, a Controlled Cooking Test (CCT) in Kampala compared the time, energy, and cost of cooking local dishes across different cookstoves, finding electric pressure cookers to be the most efficient for time-intensive foods like beans, while charcoal remained the least expensive but most time-consuming fuel (MECS).

Other studies have sought to estimate the theoretical energy required to cook specific foods. For example, Kajumba et al. (2022) estimate that cooking a kilogram of dry beans requires approximately 2.6 kilograms of firewood, while cooking maize flour requires around 1 kilogram of firewood per kilogram of food. They also report that measured energy use consistently exceeds these theoretical values due to inefficiencies in cooking environments.

Meal-based approaches to estimating cooking energy use have also emerged. Nerini et al. (2017) propose a "levelized cost of cooking a meal" model, estimating that cooking a standard meal for a family of four in Kenya requires an average of 3.6 megajoule (MJ) of final energy. Similarly, Singh et al. (2021) use aggregate energy consumption data in India to disaggregate cooking energy use by stages of meal preparation, including water heating and food boiling. Yet, these studies rarely consider the specific foods being prepared or link energy estimates to food group-level diet analysis. This study builds on these methods to estimate cooking fuel requirements and costs across food groups relevant to healthy diets in Malawi.

4.3 Cooking fuel and context in Malawi

Malawi presents an important case study for examining the role of cooking costs in shaping diets. Nearly 90% of the population relies on biomass fuels such as firewood or charcoal for cooking, with limited access to electricity or clean fuels (World Bank, 2020). The Government of Malawi has articulated ambitious goals to increase access to clean and efficient cooking technologies. The 2018 National Energy Policy prioritizes expanding the use of liquefied petroleum gas (LPG), electricity, and improved biomass stoves, aiming to reduce dependence on unsustainable charcoal and firewood harvesting (Government of Malawi, 2018). This policy framework aligns with regional and global efforts to promote clean cooking as a pathway to improved health, reduced environmental degradation, and gender equity.

Despite these goals, the clean cooking sector in Malawi faces substantial barriers. Infrastructure constraints, limited distribution networks, and the high upfront cost of cleaner cooking technologies have slowed progress. In rural areas, access to LPG and electricity remains extremely limited, while in urban areas, frequent electricity outages undermine the reliability of electric cooking (Electricity Supply Corporation of Malawi (ESCOM), 2022). Efforts to regulate charcoal production and sales have faced enforcement challenges, with charcoal continuing to serve as a dominant cooking fuel for urban households despite periodic bans (Chinangwa, 2017).

Recent donor-supported initiatives have sought to address these challenges and expand clean cooking access in Malawi. The Modern Energy Cooking Services (MECS) program has piloted electric pressure cookers and explored the feasibility of electric cooking in Malawi's energy context (MECS Programme, 2021). The World Bank and GIZ have supported programs to promote improved biomass cookstoves and develop sustainable charcoal supply

chains (World Bank, 2020). However, scaling these interventions remains difficult in the face of energy poverty, weak infrastructure, and affordability constraints for the poorest households.

As a result, biomass fuels — primarily firewood and charcoal — remain the most accessible and affordable cooking options for most Malawians. Cooking fuel constraints have important implications for gendered labor burdens. In Malawi, women typically bear primary responsibility for cooking and water and fuel collection. Recent time use surveys indicate that women in rural areas spend an average of nearly four hours per day on cooking and cleaning, in addition to approximately 45 minutes obtaining household resources (Kilic et al., 2024). Half of women and 40 percent of men collected water in the 2019-20 nationally representative household survey, compared to 17 percent and 13 percent collecting firewood (NSO, 2020b). These labor demands both reflect and reinforce gender inequalities in access to time, income-generating opportunities, and education.

These dynamics underscore the importance of understanding how cooking fuel costs and preparation requirements affect food choices and diet quality in this context. This research explores how cooking fuel costs and preparation requirements affect the cost and consumption of diverse foods needed for health in Malawi. I test the following hypotheses:

1. Cooking costs per calorie are significantly higher for starchy staples and for legumes, nuts, and seeds, relative to other food groups recommended in the HDB.
2. Incorporating cooking fuel costs will highlight the potential role of low-cost processed foods in reducing fuel use while maintaining diet quality. Specifically, I hypothesize that the composition of least-cost diets will shift when fuel costs are incorporated such that the raw foods are more expensive, but the total least-cost diet is less expensive. I test the differences between these costs using t-tests of the CoHD without cooking costs, and the CoHD food items only, selected on the basis of their total food and fuel costs.

4.4 Data and Methods

This study estimates the theoretical lower bound of household cooking fuel costs in Malawi by modeling the energy required to cook foods reported in household consumption surveys. I combine information on household food consumption from the 2019–2020 Malawi fifth Integrated Household Survey (IHS5) with data on food composition and retail prices of foods and fuels. I calculate the energy needed to cook each food based on its specific heat capacity, the quantity consumed, and the amount of water required for cooking, adjusting for local temperatures and altitude. These energy estimates are then converted into fuel requirements based on the caloric content and efficiency of common fuels in Malawi, allowing for the calculation of fuel costs. I generate four sets of estimates:

1. Lower-bound estimates of the cost of cooking individual foods, in kilojoule (KJ) per calorie, to compare the cost per calorie across food groups. These estimates provide insight into the differential cooking burden of each food group, as well as variation within the food group.

2. Lower-bound estimates of the cost associated with cooking the foods the household actually consumes, in the quantities reported in the food consumption module. These estimates demonstrate the choices households currently make.
3. Lower-bound estimates of the cost of cooking foods in a least-cost healthy diet, in quantities recommended for health (section 4.4.2). These estimates are useful for imagining how moving towards healthier diets would affect cooking costs.
4. Estimates of a least-cost healthy diet, identifying foods as least-cost by their retail price plus their lower-bound cost of cooking. These hypothetical diets can identify foods to be promoted in places and times where cooking fuel is particularly expensive, or where processing or other cooking techniques could be promoted to lower the cost of meeting food group recommendations.

4.4.1 Methods

I estimate the theoretical lower bound of energy requirements to cook individual foods. The quantity of each food consumed per household is calculated based on the total quantity reported, which is energy-adjusted and expressed in kilograms per week, aligning with the reporting period of the consumption module. The total quantity is then adjusted by the eating incidence, using household responses about how many meals are consumed per week, to estimate the cost per day. This step accounts for the economies of scale associated with fewer cooking events. Quantities consumed are further adjusted to account for inedible portions that are not cooked. It is assumed that inedible portions of animal-source foods (e.g., bones in fish and meat) are cooked but not consumed, while inedible portions of starchy staples and vegetables are discarded before cooking.

The next step involves estimating the specific heat capacity of each food, which is the amount of heat required to raise the temperature of the food by one degree Celsius, using available food composition data. The quantity of water needed to cook each food is also estimated. Based on these quantities, the theoretical energy required to heat both the food and water from ambient temperature to the boiling point of water, or the assumed cooking temperature of 90°C for food, is calculated. Using this energy requirement, the number of kilograms or units of fuel needed to supply the necessary energy is estimated, considering the calorific value of each fuel type available in Malawi and the efficiency of the stoves used. Finally, the total cost of the required fuel is calculated based on prevailing local prices.

To validate these estimates, I compare them to existing estimates in the literature. I also compare costs to the reported fuel expenditure in the household survey.

4.4.1.1 Theoretical energy requirements for cooking

I begin by estimating the specific heat capacity of individual foods, or the amount of heat needed to generate an increase of one unit in temperature to one unit of mass. Following Kajumba et al. (2022), I estimate the specific heat capacity C_i of food i (per kg of edible portion) for water (w), protein (p), total fat (f), carbohydrates (c), and ash (a):

$$C_i = 4.176w_i + 2.008p_i + 1.18f_i + 1.549c_i + 1.093a_i \tag{4.1}$$

I then estimate Ef_i, the theoretical energy needed to cook mass m (kilograms) of food i with specific heat capacity C_i from an initial ambient temperature T_{0h} ($°C$) to a final temperature T_f ($90°C$).

$$Ef_i = m_i C_i (T_f - T_{h0}) \tag{4.2}$$

I assume the initial ambient temperature T_{0h} ($°C$) is the annual mean temperature for the household h based on the geographic location of the household. Annual mean temperatures in the sample range from 18.1°C to 26.3°C. To estimate Ew_i the energy needed to boil the water needed for cooking food i, I calculate:

$$Ew_i = m_i C_i ((100 - (alt_h/300)) - T_0) \tag{4.3}$$

Given that water boils at a lower temperature at higher altitudes, I adjust the boiling point of water for altitude using household data provided in the household survey, alt_h, which ranges from 37 m to 1,652 m.

Where possible, I use the amount of water needed to cook a food from the literature. For example, water needs to cook maize, rice, plantains, cassava tubers, and beans are reported in Kajumba et al. (2022). Where there is no detailed information on the food, I estimate the water needed to cook each food depending on the food group. Details on the assumptions for the water needed to cook foods are available in the appendix 6.

The theoretical energy required to cook the food is the sum of the energy required to raise the temperature of the food and the water required to cook it to the desired temperatures, accounting for the elevation at which the food is being prepared, plus the energy needed to simmer the food. To incorporate the energy required to maintain the water at a simmer, or the food at the cooking temperature, I estimate Em as the product of the heat loss rate and an estimate of the lower bound of cooking time:

$$Em_i = q_i + t_i \tag{4.4}$$

Cooking times are estimated using cookbooks from Malawi or cooking instructions for widely consumed products like rice and pasta (Mvula, 2024; NFAM, 2022; Ibarrola de Lanuza).

The total energy is then the sum of the energy needed to raise the initial water and food temperatures and the energy needed to maintain them at the given cooking temperature:

$$E_i = Ef_i + Ew_i + Em_i \tag{4.5}$$

I then estimate the quantity Q_{if} of a given fuel f needed to transfer E_i theoretical energy to food i, given a caloric value CV_f and stove efficiency η. Assumptions about the calorific values of fuels and stoves in Malawi are reported in table 4.1.

$$Q_{if} = \frac{E_i}{CV_f \cdot \eta_f} \tag{4.6}$$

Table 4.1: Energy content and conversion efficiency of selected fuels

Fuel Name	Type	Unit	Energy content (MJ/unit)	Conversion efficiency (%)	Cooking energy (MJ/unit)
Crop residue	5% moisture	Kg	13.5	12	1.6
Firewood	Traditional, 15% moisture	Kg	16.0	15	2.4
Firewood	Efficient, 15% moisture	Kg	16.0	25	4.0
Charcoal	Traditional	Kg	30	20	6.0
Charcoal	Efficient	Kg	30	30	9.0
LPG		Kg	45.5	60	27.3
Electricity		kWh	3.6	80	2.88

Source: Bruce et al. (2017); Modern Cooking for Healthy Forests in Malawi (2020); IEA (2019); Kashyap et al. (2024).

Notes: LPG = Liquid petroleum gas.

The cost of fuel needed to prepare a given quantity of food is estimated using retail fuel prices:

$$C_{if} = Q_{if} \cdot P_{fdt} \tag{4.7}$$

where C_{if} is the total cost to purchase the quantity of fuel Q_{if} to cook food i, based on P_{flt}, the median price per kilogram of fuel f in location l and month t. For firewood and charcoal, district-level median prices are available on a monthly basis. For fuels whose prices are regulated by the government, namely LPG and electricity, I use national average prices (see section 4.4.3.3).

4.4.2 Modeled least-cost healthy diets and their cooking fuel costs

I also estimate the cooking fuel costs associated with least-cost diets, which are an important tool for understanding access to healthy diets. The CoHD is the least expensive combination of retail items available at a given time and place that meet healthy diet recommendations. This least-cost diet and its affordability are a recently developed metric of a population's physical and economic access to the foods needed for an active and healthy life. The CoHD

represents the lower bound of healthy diet costs. Incorporating preferences or convenience, such as precooked or prepared foods, is expected to add to the cost.

I use retail food prices to select the least-cost diet, for each time and place ("visit") covered in the IHS5 market survey (table 4.5). I first estimate least-cost healthy diets based on retail food prices alone, then incorporate the cost of cooking fuel required to cook each food item. I then compare the cost of the foods only to test the hypothesis that more processed or otherwise convenient foods with higher prices but lower cooking costs will be selected in the least-cost diet once cooking fuels are considered in the least-cost ranking, resulting in higher food costs.

Table 4.2: Healthy Diet Basket composition

Food group	No. of foods selected	Dietary energy (kcal)	Proportion of energy content
Starchy staples	2	1160	0.498
Oils and fats	1	300	0.129
Vegetables	3	110	0.047
Fruits	2	160	0.069
Legumes nuts and seeds	1	300	0.129
Animal source foods	2	300	0.129
Total	11	2330	1.000

Source: ?Herforth et al. (2022a).

Following the established methodology for monitoring the CoHD across countries, I use the HDB as a dietary standard. The HDB represents commonalities across most food-based dietary guidelines (FBDGs) globally Herforth et al. (2022a), which emphasize diversity within and across recommended food groups while limiting discretionary or unhealthy foods (Table I). A healthy diet is composed of eleven items across six food groups, in sufficient quantities to maintain energy balance at 2,330 calories. The energy requirement is that of an active, healthy adult woman and is similar to the average energy requirement for all sex-age-year groups aged three years and older Herforth et al. (2022a); Schneider and Herforth (2020c).

4.4.3 Data and descriptive statistics

This analysis employs data from the IHS5, implemented by the NSO in collaboration with the World Bank as part of the World Bank LSMS Integrated Surveys on Agriculture initiative. The IHS5 was conducted from April 2019 to April 2020 NSO.[1] IHSS uses agriculture, community, and household questionnaires to collect information on sample households, including all food and non-food consumption and expenditure. The survey also collects some data at the individual level, such as age, sex, occupation, level of education, and hours spent collecting water and firewood in the past 24 hours.

[1]The first cases of COVID-19 were confirmed in Malawi on 2 April 2020 UNICEF (2020).The last household survey conducted in the IHS5 was conducted on DATE. The last market survey was completed on 10 April 2020.

The IHS5 collects data on the quantity and source of food consumed by household members over the seven days before the interview. The survey contains quantities consumed, sources, and expenditure data for 142 food items. The food consumption data consists of a 7-day household recall focused on food consumed in the household (some food away from home is included, as is expenditure on restaurant meals). Nine specific types of cooked foods from vendors and meals eaten at restaurants are included. The IHS5 also collects detailed non-food expenditure data, which is combined with the information on assets and food expenditure and compiled into total consumption expenditure. The consumption aggregates, poverty categories, and spatial and temporal deflators provided allow us to classify households as poor and non-poor within the survey and compare their expenditures across the survey period.

Respondents were asked about the household's primary source of fuel for cooking, selecting either collected firewood, purchased firewood, paraffin, electricity, gas, charcoal, crop residue, sawdust, or other (unspecified). A separate question was asked about the primary source of fuel for lighting.

Table 4.3: Household characteristics

tab:hhdescriptp2)

	Region			
	North	Central	South	Total
Sample size	526,949 (12.9%)	1,709,207 (41.7%)	1,861,917 (45.4%)	4,098,073 (100.0%)
Rural (0/1)	0.83 (0.4)	0.83 (0.4)	0.84 (0.4)	0.84 (0.4)
Household size	4.46 (2.3)	4.50 (2.0)	4.30 (2.0)	4.40 (2.0)
Head age (years)	44.20 (16.2)	42.42 (15.6)	43.54 (16.7)	43.16 (16.2)
Head educ. (years complete)	7.78 (3.9)	6.05 (4.4)	5.75 (4.5)	6.13 (4.4)
Poor (0/1)	0.25 (0.4)	0.49 (0.5)	0.42 (0.5)	0.42 (0.5)
Total expenditure	4.40 (5.0)	3.19 (5.5)	3.38 (4.1)	3.43 (4.8)
Share of expenditure on food	0.66 (0.2)	0.67 (0.2)	0.66 (0.2)	0.67 (0.2)
Dist. to *boma* market	41.55 (34.6)	24.43 (14.8)	22.12 (17.5)	25.58 (20.6)
Dist. to pop center	26.26 (17.5)	21.61 (13.4)	18.99 (13.3)	21.02 (14.2)
Dist. to agric. market	23.58 (15.1)	26.58 (15.4)	18.12 (12.0)	22.35 (14.5)
Elevation (m)	1088 (338)	1068 (249)	705 (269)	906 (327)
Annual mean temperature	20.87 (2.1)	20.57 (1.5)	22.47 (1.6)	21.47 (1.9)

Note: Poor (0/1) is based on having total expenditure below the national poverty line. Expenditure is in 2021 PPP/AE/day per day. All distances are to the nearest place in kilometers. Annual mean temperature is in Celsius.

The majority of households in Malawi live in rural areas, with the largest population concentrated in the Southern and Central regions. The Northern region of Malawi has the smallest population, fewer households living below the national poverty line, but higher average educational higher educational attainment among household heads. The Southern region is the most populous region, with two of the country's major cities, and is warmer and at a lower elevation than the other parts of the country. The Southern region is also the most densely populated, such that households live closer to larger towns, population centers, and agricultural markets than they do in the Central and Northern regions (Table 4.3tab:hhdescriptp2).

Less than half (46%) of urban households have access to electricity in their home, compared to only 4% of households in rural areas. Of urban households that do have access to electricity, only 6% report using it as their main cooking fuel (Table 4.4). It follows that very few households have access to electric and gas stoves, refrigerators, or electric kettles in rural areas.

Table 4.4: Descriptive statistics on fuel use and cooking infrastructure

		Rural (0/1)		
	Urban	Rural	Total	Test
Sample size	2,074	9,316	11,390	
Electricity in home (0/1)	0.46 (0.5)	0.04 (0.2)	0.11 (0.3)	<0.001
Main cooking fuel				
Crop residue (0/1)	0.00 (0.0)	0.01 (0.1)	0.01 (0.1)	<0.001
Collected firewood (0/1)	0.11 (0.3)	0.85 (0.4)	0.73 (0.4)	<0.001
Purchased firewood (0/1)	0.08 (0.3)	0.06 (0.2)	0.07 (0.2)	0.196
Charcoal (0/1)	0.74 (0.4)	0.07 (0.3)	0.18 (0.4)	<0.001
Liquid petroleum gas (0/1)	0.00 (0.0)	0.00 (0.0)	0.00 (0.0)	0.057
Electricity (0/1)	0.06 (0.2)	0.00 (0.0)	0.01 (0.1)	<0.001
Time to walk from dwelling to collect firewood (hours, one way)	0.06 (0.3)	0.41 (1.3)	0.22 (0.9)	<0.001
Cooking water in yard/plot (0/1)	0.37 (0.5)	0.04 (0.2)	0.09 (0.3)	<0.001
Time to walk from dwelling to main water source (hours, one way)	0.11 (0.5)	0.19 (0.5)	0.18 (0.5)	<0.001
Own kerosene/paraffin stove (0/1)	0.00 (0.1)	0.00 (0.0)	0.00 (0.0)	0.108
Own electric/gas stove (0/1)	0.12 (0.3)	0.01 (0.1)	0.03 (0.2)	<0.001
Own fridge (0/1)	0.21 (0.4)	0.02 (0.1)	0.05 (0.2)	<0.001
Own electric kettle (0/1)	0.13 (0.3)	0.01 (0.1)	0.03 (0.2)	<0.001

Note: Expenditure is in 2021 PPP per AE per day.

Almost three-quarters of households in Malawi rely on collected firewood as their main cooking fuel. In rural areas, nearly all households use firewood as their main cooking fuel, and live a 25-minute walk from their main firewood collection source on average. The majority of urban households use charcoal as their primary cooking fuel.

4.4.3.1 Market prices in the IHS5

The IHS5 also collected retail price data from markets concurrently with the household survey. Prices were collected for 138 food consumption items across 377 markets. The item list corresponds closely to the list included in the IHS5 food consumption module. Up to three samples were collected from different vendors for each item-unit combination, with weights and prices recorded for each sample NSO, 2023). A total of 330,429 price observations were recorded across the country (table 4.5).

Table 4.5: Market survey descriptives

Observations (N)	North	Central	South	Total
Total markets	55	151	171	377
Rural markets	47	113	142	302
Visits	174	394	503	1071
Food items	132	136	129	138
Retail food prices	70,880	133,209	126,340	330,429

Source: NSO (2023) and authors' calculations. Note: The market survey collected crop prices as well as retail food prices.

4.4.3.2 Food composition data

I match each food in the household consumption module and in the IHS5 market survey to an item in a food composition database for the specific heat capacity calculations and for calculating the price per kilocalorie (kcal) for least-cost healthy diets. Food composition data comes primarily from the Malawi Food Composition Table 2019, the United States Department of Agriculture (USDA Agricultural Research Service, 2016b; USDA ARS), and the West African Food Composition Table 2020.

4.4.3.3 Fuel price data

I use retail fuel price data from the NSO of Malawi for monitoring inflation with the Consumer Price Index. The price data is collected in all major trading centers and cities across the country, namely 22 towns/trading centers selected to represent rural areas, and in 6 markets across the four cities to represent urban areas (two markets each are visited in Lilongwe and Blantyre, while only one market is visited in each Zomba and Mzuzu). More detail on the price data can be found in Appendix 6.

The NSO collects retail prices for firewood and charcoal monthly, as described for food prices collected in markets. Firewood and charcoal prices are originally collected for non-standard units of the fuels, such as bundles of firewood or bags of charcoal, and converted into average unit prices per kilogram after purchase by the price collectors. I also compile fuel price data for LPG and electricity from the Malawi Energy Regulatory Authority (MERA) and Electricity Supply Corporation of Malawi (ESCOM), respectively. LPG and electricity prices are regulated by MERA. [2]

4.5 Results

4.5.1 Food group cooking costs

The theoretical energy needed to cook each food depends on the specific heat capacity (equation 4.1), the quantity of water needed to prepare it, and the annual mean temperature and elevation of the market or household. The average specific heat capacity is highest for

[2] For more detail on nationally regulated fuels, see Appendix 6.

fruits and vegetables, which have more water weight than other food groups (figure 4.1). While fruits are mostly consumed raw, vegetables are usually cooked in Malawi. Starchy staples, legumes, nuts, and seeds have low specific heat capacity due to their low moisture. Animal source foods have a relatively high average specific heat capacity, partly because protein contributes more to specific heat than carbohydrates or fats.

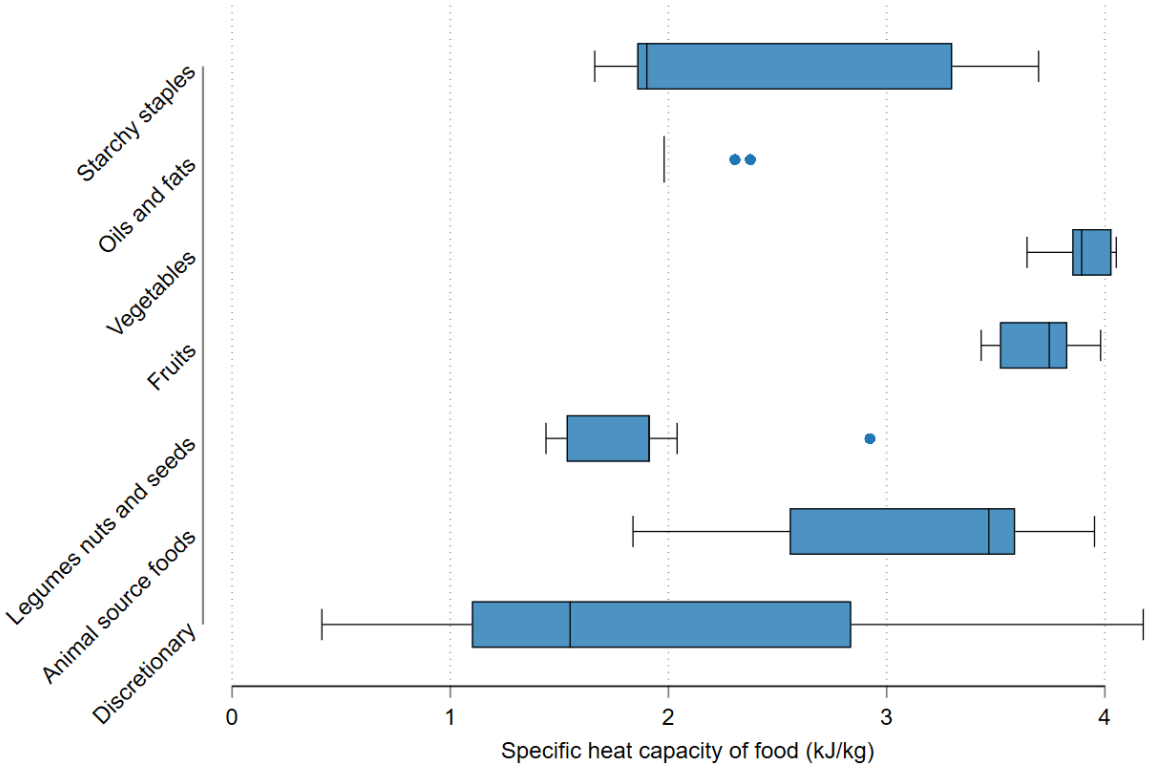


Figure 4.1: Specific heat capacity, by food group

The six HDB food groups have statistically significantly different theoretical energy needs (figure 4.2). Relative to starchy staples, which account for most calories consumed, vegetables, legumes, nuts and seeds, and animal-source foods have higher overall theoretical energy requirements. While the differences are driven by energy requirements for maintaining food and water at a cooking temperature for all three food groups, vegetables also have a significantly higher theoretical energy requirement based on food composition alone.

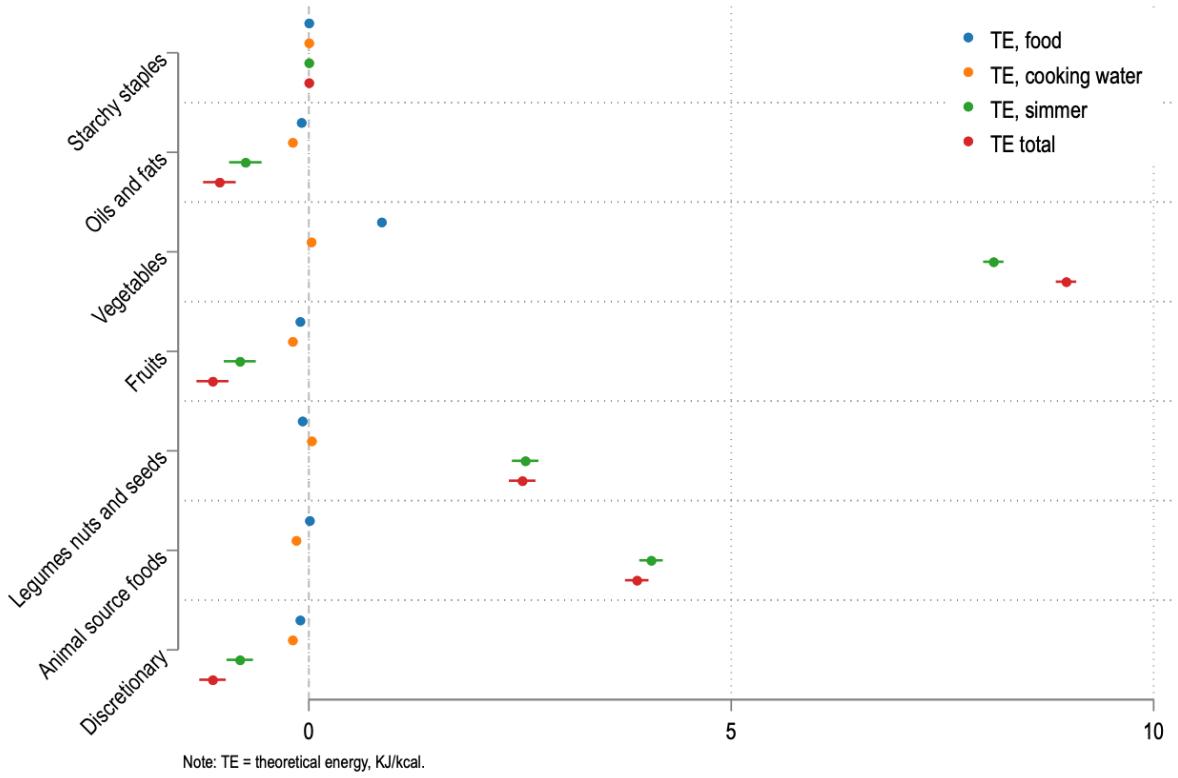


Figure 4.2: Theoretical energy per calorie, by food group

Vegetables have the highest theoretical energy needs on a per-calorie basis (10 KJ/kcal), given their low energy density, high moisture content, and moderate cooking water needs. Animal-source foods and legumes, nuts, and seeds have the next largest theoretical energy needs per calorie, at 5.13 and 3.77 KJ/kcal, respectively. See Appendix 6 for item-level estimates.

4.5.2 Reported diets

Estimates of the total theoretical energy needed for cooking the foods households reported eating in the last week are statistically significantly different in rural and urban areas, controlling for the size and composition of the household with adult equivalents. Lower-bound energy needs to maintain the foods at cooking temperatures are lower in rural areas, suggesting less time-intensive foods or cooking techniques than urban areas (figure 4.3). However, there is no statistically significant difference between urban and rural areas in the Northern region, and regions themselves do not have statistically significantly different theoretical energy needs overall. The Northern region has higher lower-bound cooking costs in terms of the energy needed to bring the food alone to a cooking temperature, due to higher consumption of some high-specific heat starchy staples (plantains, cocoyam) and animal-source foods (fresh dairy and fresh fish). [3]

[3]See Appendix 6 for regression results.

Table 4.6: Characteristics of all foods, per food group

	Specific heat capacity	TE, food	TE, water	TE, simmer	TE, total	N
Starchy staples	2.49	0.11	0.19	0.82	1.14	40,792
	(0.74)	(0.10)	(0.13)	(1.71)	(1.81)	
Oils and fats	2.01	0.02	0.00	0.07	0.08	10,463
	(0.09)	(0.00)	(0.00)	(0.09)	(0.09)	
Vegetables	3.90	0.96	0.22	8.92	10.10	48,236
	(0.10)	(0.40)	(0.22)	(14.97)	(15.01)	
Fruits	3.67	0.00	0.00	0.00	0.00	11,258
	(0.29)	(0.00)	(0.00)	(0.00)	(0.00)	
Legumes nuts and seeds	1.78	0.03	0.23	3.38	3.67	21,671
	(0.28)	(0.01)	(0.12)	(5.36)	(5.38)	
Animal source foods	3.13	0.11	0.04	4.87	5.02	27,587
	(0.63)	(0.08)	(0.09)	(8.42)	(8.46)	
Discretionary	1.81	0.00	0.00	0.00	0.00	41,283
	(1.25)	(0.00)	(0.00)	(0.00)	(0.00)	
Total	2.74	0.31	0.14	3.84	4.29	35,579
	(1.10)	(0.46)	(0.17)	(9.54)	(9.73)	

Note: TE = theoretical energy in KJ/kcal, assuming all cooking done with firewood.

4.5.2.1 Lower-bound energy needs for cooking reported diets, for all food groups and all fuel sources

Estimated cooking costs per calorie are highest for vegetables and animal-source foods, which have high theoretical cooking costs and are commonly consumed.

The total estimated fuel cost to cook reported foods for a household is based on their calorie allocation to each food group and the theoretical fuel needs for that group. Food groups that are consumed in larger quantities, such as starchy staples and legumes, nuts and seeds, drive total costs. However, vegetables have a significantly higher cooking cost on a calorie of food consumed basis - on average, cooking a calorie of vegetables can be 10 times more expensive than cooking a calorie of starchy staples.

Assuming that each household uses one cooking fuel for all cooking needs, the cost of meeting theoretical energy needs for cooking is shown at the level of the Traditional Authority (figure 4.4). Lower bound cooking costs associated with reported diets in Malawi vary significantly by fuel type, ranging from 0.041-1.85 international dollars (2021 PPP) per household per day. Electricity and charcoal are less expensive than firewood and LPG.

High costs associated with LPG are driven by high prices per unit of energy (figure 4.5). Despite declining tariff rates for LPG beginning in mid-2018, the unit cost per LPG ranged from 0.13-0.24 PPP/MJ, compared to 0.01-0.06 PPP/MJ for the other three fuels.

As noted earlier, both LPG and electricity were largely unavailable in rural areas at the time of the surveys, and were rarely reported as the main cooking fuel. The volatility of firewood prices is also evident in Figure 4.5, particularly relative to charcoal prices, which are also unregulated yet remain stable throughout the 2018-2020 period. Electricity tariffs were adjusted upwards in early 2018, but remained constant for the majority of the survey period. Appendix 6 provides additional detail on MERA regulation of electricity and LPG

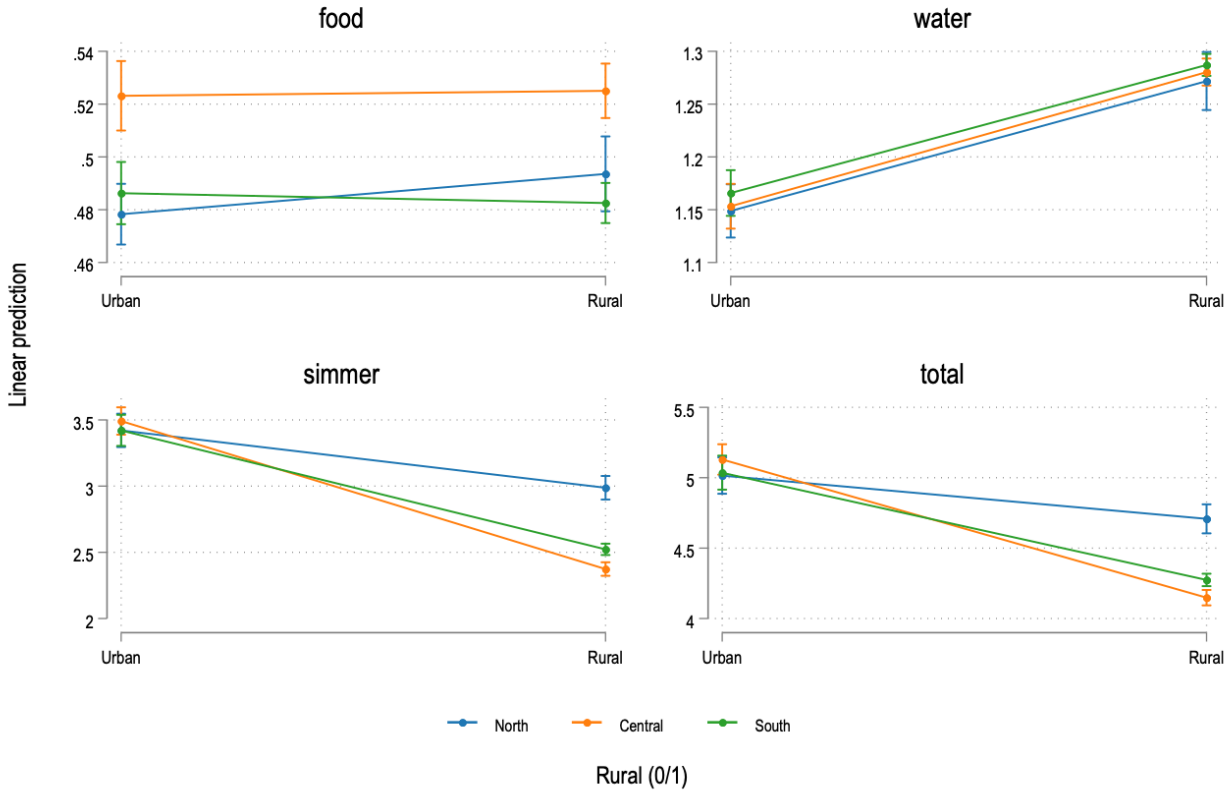


Figure 4.3: Margins plot for lower-bound energy needs for cooking reported diets, by rural-region

Notes: OLS regression of theoretical energy needs (MJ), controlling for household adult equivalents. Robust standard errors and household sampling weights applied.

tariffs.

Table 4.7: Cost per calorie and total cost, by food group and cooking fuel

		Cost per 100 kcal		Total fuel cost per household	
	Calories	Firewood	Charcoal	Firewood	Charcoal
Starchy staples	1551	0.05	0.03	0.27	0.18
	(382)	(0.1)	(0.0)	(0.2)	(0.1)
Oils and fats	118	0.00	0.00	0.00	0.00
	(110)	(0.0)	(0.0)	(0.0)	(0.0)
Vegetables	47	0.55	0.30	0.08	0.05
	(46)	(0.7)	(0.3)	(0.1)	(0.0)
Fruits	30	0.00	0.00	0.00	0.00
	(48)	(0.0)	(0.0)	(0.0)	(0.0)
Legumes nuts and seeds	203	0.08	0.04	0.16	0.08
	(206)	(0.1)	(0.1)	(0.2)	(0.1)
Animal source foods	65	0.15	0.08	0.08	0.04
	(72)	(0.3)	(0.1)	(0.1)	(0.1)
Discretionary	90	0.00	0.00	0.00	0.00
	(102)	(0.0)	(0.0)	(0.0)	(0.0)

Note: Costs are in 2021 PPP. Cost is based on reported diets for a household, if all cooking were done with one fuel. This table does not consider the main cooking fuel of the household, but rather assumes all households use firewood or all households use charcoal.

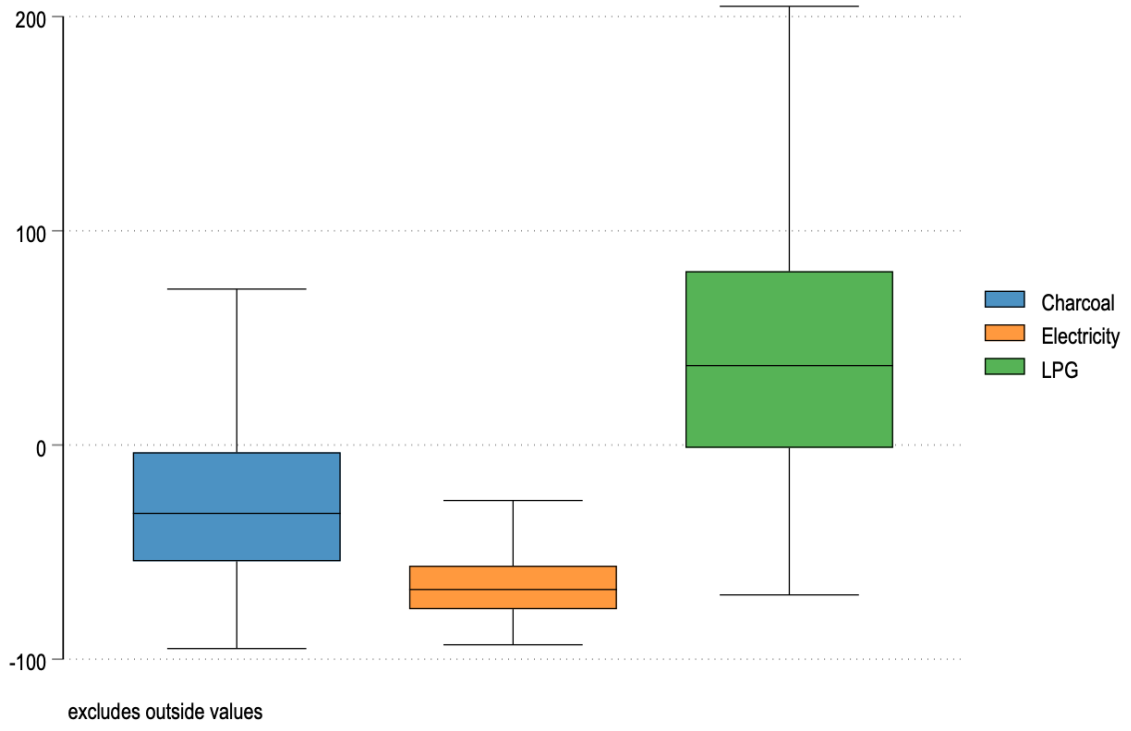


Figure 4.6: Percent difference in cost between firewood and other fuels
Notes: Negative values represent households where firewood is more expensive than the other fuel, in terms of total cost to prepare food (2021 PPP/AE/day). Firewood is the most commonly used cooking fuel in Malawi. Outliers are excluded from the figure.

On average, cooking with purchased firewood is about 25% and 65% more expensive than cooking with charcoal and electricity, respectively.Cooking entirely with firewood is 48% less expensive than cooking entirely with LPG (Figure 4.6).

4.5.2.2 Lower-bound cooking costs for reported diets, with main cooking fuel

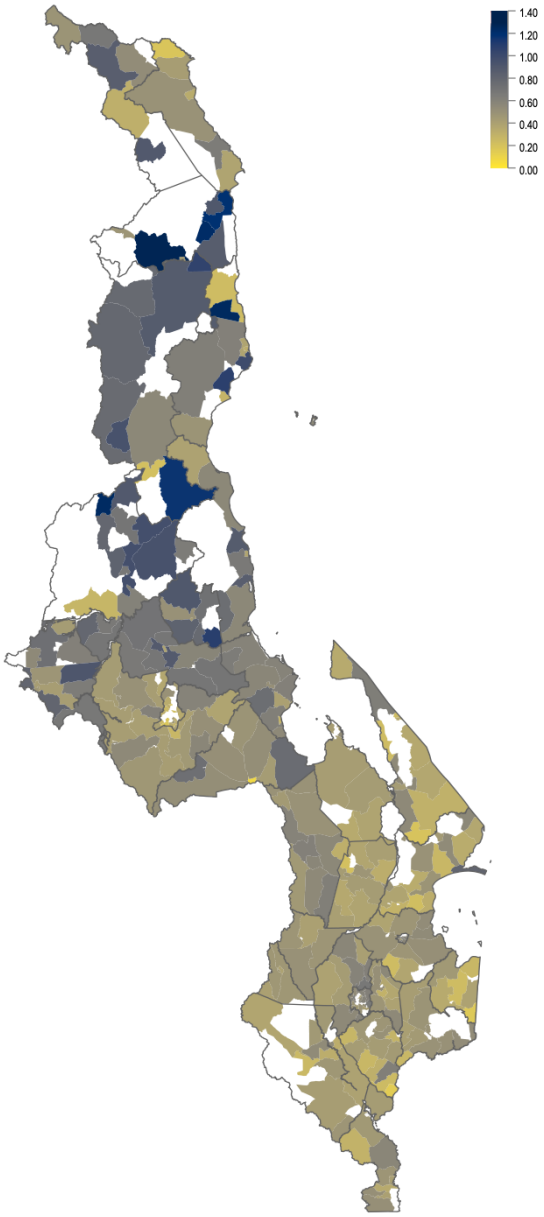


Figure 4.7: Lower bound cooking costs for reported diets, with main cooking fuel

When considering only the fuel households report as their main cooking fuel, the average lower-bound estimate of cooking fuel costs is 0.17 PPP per adult equivalent per day (table 4.8). The locations with the highest fuel costs are in the central and northern regions (figure 4.7). However, urban areas in the South and rural areas in the North experience the highest costs, all else equal, controlling for household size, fuel prices, and their choice of primary cooking fuel. Rural areas in the north rely on firewood, while the urban south relies most heavily on charcoal.

Differences in electricity and LPG costs reflect different theoretical energy needs across the small number of households that use these as their main cooking fuel; these results should be interpreted with caution. Furthermore, all estimates assume all foods are cooked using the same fuel, which is likely unrealistic except for in the poorest households who only have access to firewood. Without information on use of multiple fuels for cooking or stove stacking, it is difficult to make assumptions about household fuel use, aside from examining total fuel expenditures for cooking and heating.

Table 4.8: Least-cost cooking energy for reported diets, per adult equivalent, using main fuel

	(1)	(2)
	Lower bound fuel cost	Lower bound fuel cost
Central	-0.027***	0.044***
	(0.006)	(0.007)
South	0.025***	0.088***
	(0.006)	(0.007)
Rural	0.062***	0.085***
	(0.009)	(0.008)
Central × Rural	-0.026***	-0.083***
	(0.009)	(0.009)
South × Rural	-0.133***	-0.120***
	(0.009)	(0.008)
Main fuel = Electricity	-0.138***	-0.135***
	(0.006)	(0.007)
Main fuel = LPG	0.079***	0.079**
	(0.021)	(0.039)
Main fuel = charcoal	-0.054***	-0.053***
	(0.003)	(0.003)
Adult equivalent (based on 2330 kcal/day) (hh)	-0.025***	-0.026***
	(0.001)	(0.001)
Price of firewood (MWK/kg)		0.002***
		(0.000)
Price of charcoal (MWK/kg)		0.000***
		(0.000)
Price of LPG (MWK/kg)		0.000***
		(0.000)
Constant	0.281***	-0.190***
	(0.007)	(0.015)
Mean	0.17	0.17
N	11270	11270
F-Stat	179.04	265.22

Note: Robust standard errors with household weights.

4.5.3 Least-cost diets

Using the market data collected alongside the household survey, 1,002 of the 1,071 market visits had enough food items available to complete a least-cost healthy diet, as defined by the HDB. The average CoHD across the market visits was 652 MWK per person per day, or 2.56 PPP. The CoHD ranged from 1.26 to 5.11 PPP at the market-visit level.

Table 4.9: Test of CoHD differences with fuel incorporated, by fuel type

	(1) Total CoHD	(2) Food cost only	(3) Fuel cost only
Firewood	1.038***	0.311***	
	(0.033)	(0.027)	
Electricity	0.058**	0.001	-0.670***
	(0.025)	(0.025)	(0.019)
LPG	0.226***	0.013	-0.513***
	(0.025)	(0.025)	(0.019)
Charcoal	0.131***	0.006	-0.602***
	(0.025)	(0.025)	(0.019)
Constant	2.563***	2.563***	0.727***
	(0.017)	(0.017)	(0.019)
Mean	2.85	2.63	0.28
N	5005	5005	4004
F-Stat	268.74	48.76	3202.33

Note: Baseline is the Cost of a Healthy Diet without fuel costs considered. For the baseline CoHD, the cost per food per day and the CoHD are equivalent. Robust standard errors.

Adding in the lower-bound estimate of the cost of fuel to cook the least-cost items significantly increases food costs if firewood is assumed to be the main cooking fuel (Table 4.9). The food costs change when the least-cost items are identified using the cost of the food plus the fuel costs, rather than the food cost alone. The average CoHD without fuel costs is 2.56 PPP; the CoHD increases by an average of 0.31 PPP in food costs alone when the least-cost items are selected based on food and firewood costs. For all other cooking fuels, food costs for the least-cost items are not statistically significantly larger when fuel costs are considered.

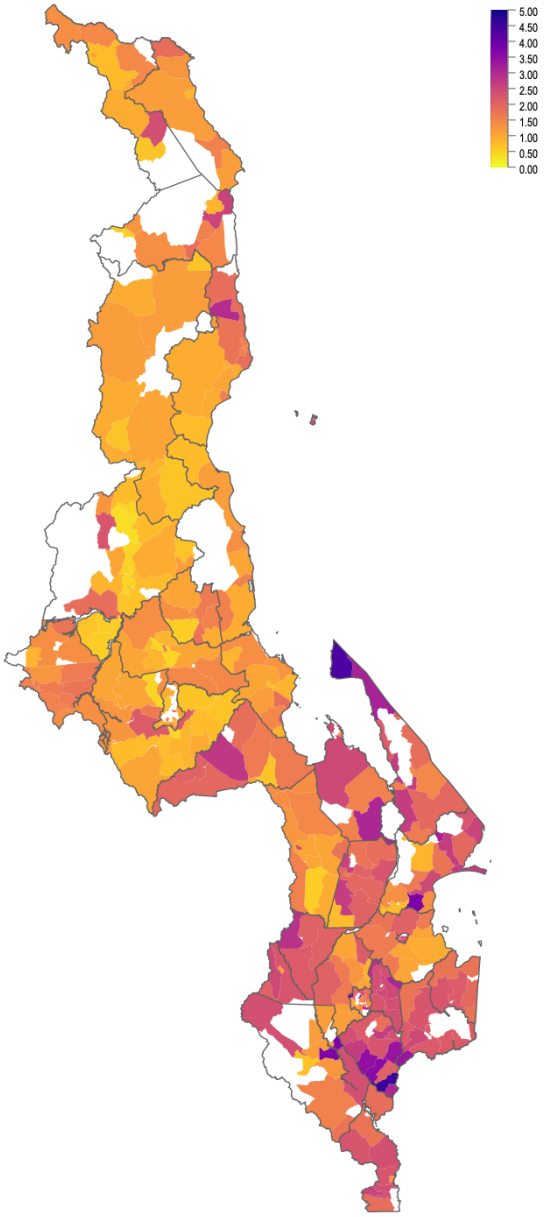


Figure 4.8: Difference in CoHD, with and without fuel costs

Notes: Figure shows differences in 2021 PPP between the CoHD identified by account for food and lower-bound cooking fuel costs, relative to the CoHD calculated using only food prices.

This is due in part to substitution from high cooking-cost foods to items with items in the food group with lower or no cooking fuel costs per calorie, such as prepared foods. For example, boiled eggs sold by vendors are the most frequently substituted animal-source food when fuel costs are incorporated into the CoHD calculation, followed by powdered and liquid milk. In the starchy staples category, the most common substitution is from rice to white bread. Other common substitutions are towards roots and tubers, and prepared foods like *zikdonamoyo*, a prepared snack made with banana, flour, and egg.

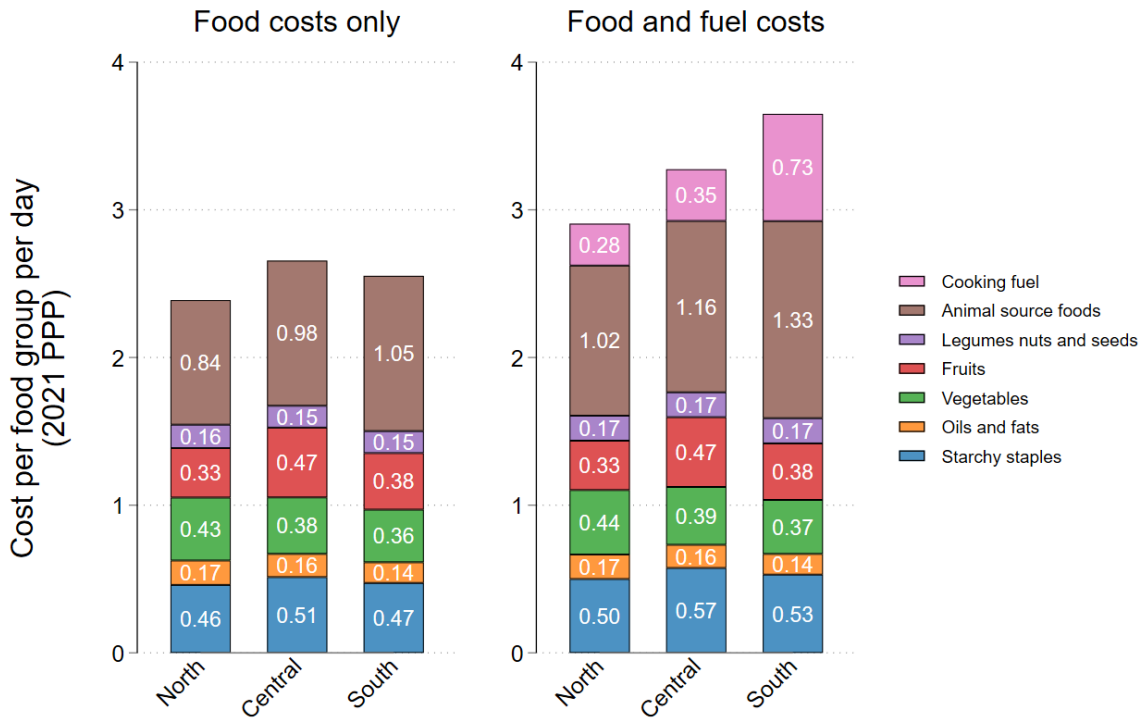


Figure 4.9: Contribution of food groups and fuel to least-cost healthy diets
Notes: N = 1001 market-visits for which there is data for all both food and fuel prices, and complete least-cost diets, as defined by a total of 2,330 calories across 6 food groups.

Figure 4.9 shows that the difference between least-cost diets stems primarily from changes to the animal-source foods and oils and fats categories. Detailed results by district are presented in Appendix 6.

A comparison of the theoretical energy costs to prepare reported diets and those required for least-cost diets suggests that households could consume healthy diets and reduce cooking costs by consuming foods within the same food group that require less cooking time, largely due to lower water and cooking times, as well as preparing lower moisture foods. This is true across all areas of the country.

Likely more important would be to consume diets in line with food group recommendations. Malawian households consume considerably more calories from starchy staples than is rec-

Table 4.10: Theoretical energy needs per day, least-cost healthy diets

	Reported diets				Least-cost diets			
	Food	Water	Simmer	Total	Food	Water	Simmer	Total
Urban North	0.46	1.10	3.41	4.93	0.14	0.18	0.62	0.93
	(0.29)	(0.71)	(1.43)	(1.85)	(0.04)	(0.06)	(0.17)	(0.25)
Urban Central	0.52	1.16	3.50	5.09	0.16	0.20	0.68	1.03
	(0.30)	(0.63)	(1.34)	(1.79)	(0.04)	(0.07)	(0.19)	(0.26)
Urban South	0.47	1.12	3.40	4.95	0.15	0.20	0.84	1.17
	(0.25)	(0.64)	(1.43)	(1.80)	(0.03)	(0.08)	(0.37)	(0.45)
Rural North	0.51	1.32	3.00	4.78	0.17	0.21	0.80	1.17
	(0.31)	(0.80)	(1.33)	(1.82)	(0.04)	(0.06)	(0.23)	(0.30)
Rural Central	0.54	1.31	2.38	4.17	0.15	0.20	0.77	1.11
	(0.35)	(0.69)	(1.29)	(1.71)	(0.04)	(0.06)	(0.33)	(0.38)
Rural South	0.46	1.24	2.51	4.20	0.18	0.23	0.95	1.34
	(0.30)	(0.66)	(1.29)	(1.60)	(0.05)	(0.08)	(0.38)	(0.44)
Total	0.50	1.26	2.67	4.38	0.16	0.21	0.84	1.20
	(0.32)	(0.69)	(1.37)	(1.73)	(0.04)	(0.07)	(0.35)	(0.41)
Observations	11432	11432	11432	11432	11432	11432	11432	11432

Note: Theoretical energy is the lower-bound estimate of cooking energy needed (MJ/day). Reported diets shown here are for firewood, the most common main cooking fuel in Malawi.

ommended. Households would also need to scale up fruit and vegetable consumption, which is well below recommended levels. The transition away from starchy staples and towards fruits and vegetables would be nutritionally positive, with relatively small impacts on total cooking costs if vegetables are consumed raw (e.g., cucumber) or prepared with less cooking time or more efficient fuels.

Households that struggle to access affordable cooking fuels can be encouraged to consume prepared, healthy ASF, such as dairy, boiled eggs, and small dried fish.

4.6 Discussion

This study provides the first nationally representative estimates of cooking fuel costs associated with both reported diets and least-cost healthy diets in Malawi. By modeling lower-bound energy requirements to cook foods, this work takes initial steps toward quantifying the role of cooking costs in shaping diet affordability and composition, with several key findings.

First, the cost to cook a calorie is not uniform across food groups. Cooking costs per calorie are highest for vegetables, due to their high water content and low energy density, followed by animal-source foods and legumes, nuts and seeds. While starchy staples are relatively efficient to cook on a per-unit basis, their large contribution to overall calorie intake drives

Table 4.11: Calories and fuel costs per food group per day

	Reported diets		Least-cost diets	
	Calories	Fuel cost	Calories	Fuel cost
Starchy staples	1704.10	0.09	1160.00	0.21
	(336.69)	(0.06)	(0.00)	(0.11)
Oils and fats	160.74	0.00	300.00	0.04
	(114.62)	(0.00)	(0.00)	(0.01)
Vegetables	48.78	0.03	110.00	0.13
	(53.89)	(0.03)	(0.00)	(0.05)
Fruits	55.36	0.00	160.00	0.00
	(60.96)	(0.00)	(0.00)	(0.00)
Legumes nuts and seeds	259.78	0.07	300.00	0.08
	(221.36)	(0.08)	(0.00)	(0.31)
Animal source foods	90.09	0.04	300.00	0.26
	(83.21)	(0.06)	(0.00)	(0.51)
Exclude	104.34	0.00		
	(112.70)	(0.00)		
Total	375.36	0.03	388.33	0.12
	(611.61)	(0.06)	(353.23)	(0.27)
Observations	70702	70702	6006	6006

Note: Costs are in 2021 PPP. Reported diets shown here are for firewood, the most common main cooking fuel in Malawi.

total cooking costs at the household level in Malawi, where maize-based *nsima* is a staple food.

Second, incorporating lower-bound cooking fuel costs into the CoHD alters the composition of least-cost modeled diets. When firewood costs for cooking are considered alongside retail food prices, least-cost foods identified shift from raw foods with high cooking requirements toward processed or pre-cooked alternatives. For example, rice is replaced with bread among starchy staples, while boiled eggs, powdered milk, or dried fish enter least-cost diets in the animal-source foods group. These substitutions raise the average price per calorie of selected foods but lower total fuel needs, consistent with a cost-minimizing strategy that accounts for both food and energy inputs.

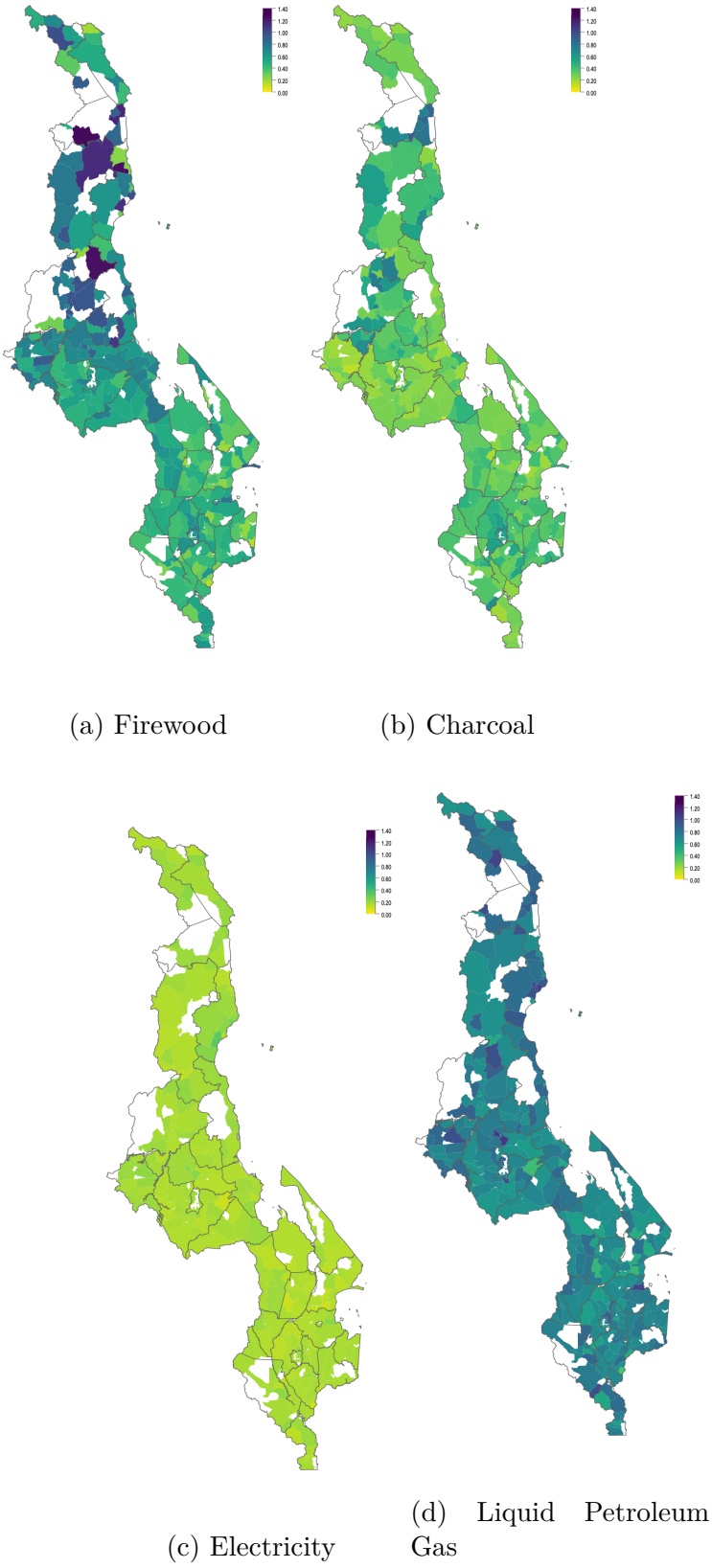
Third, variation in cooking costs across food groups and fuel types is large enough to significantly influence both the relative cost and composition of healthy diets. Access to less costly fuels like electricity, or lower costs for highly efficient fuels like LPG, could have a considerable impact. These fuels are inaccessible to most households in Malawi, and elsewhere in low-income countries, but could help households deal with volatile firewood prices, declining fuel wood availability, and the environmental and health costs associated with charcoal.

The findings suggest that cooking energy requirements are an important but often overlooked factor in assessing food affordability and promoting dietary change. Policy interventions promoting access to efficient cooking technologies, such as electric pressure cookers or clean-burning stoves, could reduce the burden of cooking energy, especially for vegetables and ASF. Promoting ready-to-eat or lightly processed foods — such as boiled eggs, fortified dairy, or roasted legumes may also offer a practical path toward improving diet quality without significantly increasing household energy use or costs.

4.6.1 Limitations and future research

Meal preparation costs that are not included in this analysis include washing, chopping, or otherwise preparing food for cooking. I hypothesize that the time spent in these activities is large and varies across food groups in significant ways; for example, many leafy greens are removed from the stem or deveined in traditional Malawian cooking, a time-consuming step. The slaughter, dressing or other preparation of animal-source foods like chickens or fish can be time-consuming, and require large amounts of water relative to cooking, which may impose high costs for households that do not have access to piped water.

These estimates also point to the data gaps and the potential for improved policy, programming, and research that takes advantage of the extensive work on cookstoves and cooking energy to better understand how this impacts not only respiratory health but also health from a dietary intake perspective.



(a) Firewood (b) Charcoal

(c) Electricity (d) Liquid Petroleum Gas

Figure 4.4: Lower bound cooking costs for reported diets, by fuel type
Notes: Costs are 2021 PPP/day.

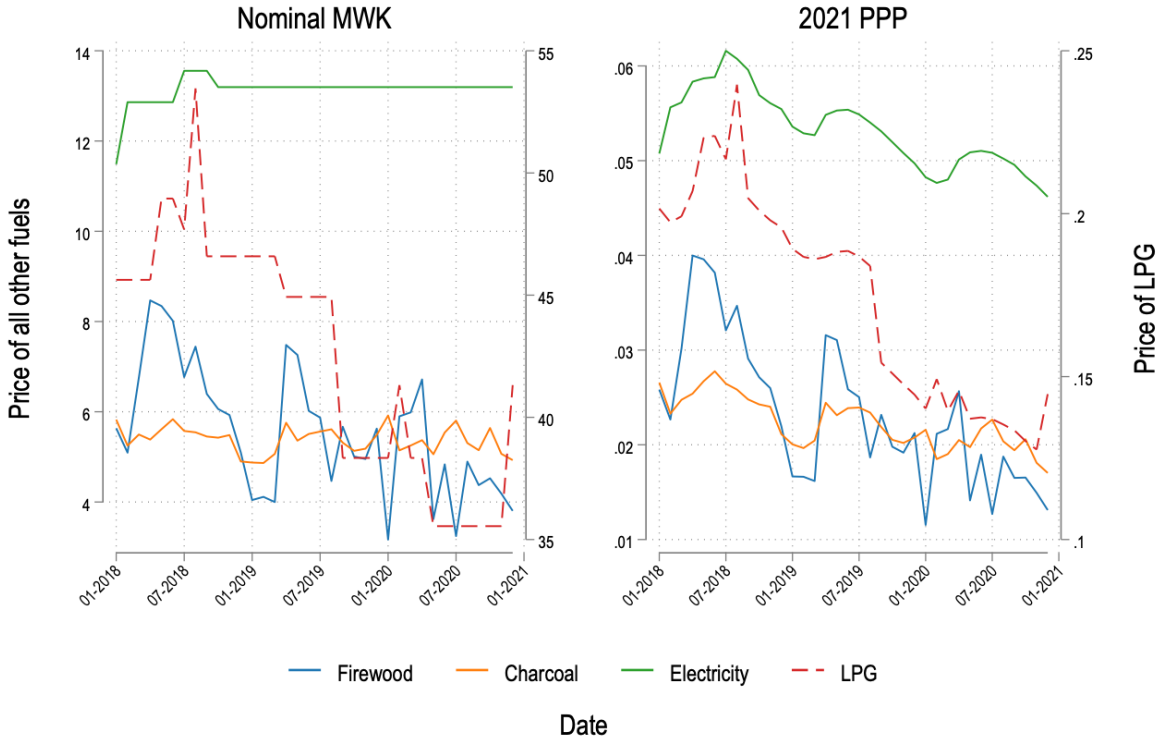


Figure 4.5: Monthly fuel prices

Source: Authors' calculations using data from the National Statistical Office of Malawi and Malawi Energy Regulatory Authority.

Notes: Average prices are in MWK/MJ (left) and 2021 PPP/MJ (right). 1 USD PPP, 2021 = 282 MWK.

Chapter 5

Conclusions

This dissertation demonstrates how the affordability of healthy diets continues to shape consumer food choices in low- and lower-middle-income countries, particularly in Malawi and the eight WAEMU countries. Despite global concerns about diet-related noncommunicable diseases (NCDs), many of these countries remain at an earlier stage of the dietary transition, where affordability still determines access to nutritious diets.

In Malawi, we find that households' revealed preferences for more nutritious foods align with health needs in some regards and diverge in important ways. Increased purchasing power leads to improvements in diet quality. However, among higher-income households, food choices increasingly reflect the same behavioral and informational failures observed in other countries: people tend to overspend on animal-source foods, oils, and discretionary items including sweets, while under-consuming fruits, vegetables, and legumes. These patterns reflect the reality that individuals cannot see or sense the long-term health value of their food, and food environments often mislead consumers through taste, price, and convenience.

In the WAEMU countries, the situation differs. There, we find that income strongly improves diet quality across nearly all population groups, including wealthier urban households. Because most of these populations remain well below international poverty thresholds and food systems are still relatively traditional, gains in household income and reductions in food prices translate into higher consumption of foods aligned with dietary guidelines. This aligns with past findings by McCullough and stands in contrast with upper-middle-income countries, where increases in affordability often lead to overconsumption of unhealthy foods and lower overall diet quality.

This study also provides the first nationally representative estimates of cooking fuel costs associated with both reported diets and least-cost healthy diets in Malawi. By modeling lower-bound energy requirements to cook foods, this work takes initial steps toward quantifying the role of cooking costs in shaping diet affordability and composition. Three key findings emerge. First, cooking costs per calorie vary across food groups, with vegetables being the most expensive due to their low energy density and high water content. Second, incorporating cooking costs into the CoAHD framework alters the composition of modeled diets, favoring more energy-efficient foods such as bread, powdered milk, and dried fish over

foods that require more cooking energy. Third, large variation in cooking costs across fuel types suggests that improving access to efficient fuels like electricity or LPG could significantly reduce household energy burdens and influence diet composition.

These results offer timely insights for policy. For governments and donors, the evidence supports dual strategies: (1) demand-side interventions such as safety nets and food-based transfers to ensure affordability for vulnerable groups, and (2) supply-side investments to reduce the real cost of nutritious foods. For agricultural development stakeholders—such as the Gates Foundation—these findings reinforce the importance of productivity gains across all food groups to reduce consumer prices and improve access to nutritious diets.

The novelty of this research lies in demonstrating how demand for healthy diets responds to changes in overall affordability. Unlike studies focused narrowly on individual food subsidies or taxes, this work captures a broader interplay of food demand elasticities across six key food groups, discretionary foods, and total calorie budgets. It also incorporates the energy costs of meal preparation, expanding the traditional concept of food affordability to include both food and fuel expenditures. In low-income settings, spending power is limited not only by money but also by time and energy constraints. This study models how improving affordability—through higher incomes, lower food prices, or reduced cooking costs—allows households to rebalance their diets toward more healthful compositions.

These findings have implications for ongoing transitions in food systems. As countries like Malawi and those in the WAEMU region continue to develop, policymakers must anticipate shifts in food preferences and consumption patterns. While affordability remains a primary constraint today, the future may resemble more advanced economies, where unhealthy dietary transitions emerge unless guided by smart regulation, consumer education, and structural changes in the food environment. Policy interventions promoting access to efficient cooking technologies—such as electric pressure cookers or clean-burning stoves—and promoting lightly processed, ready-to-eat foods like boiled eggs or fortified dairy could facilitate better dietary outcomes without imposing additional burdens on household energy use.

Future Research

This research highlights key avenues for further investigation. First, better data on the middle segments of agri-food value chains could illuminate how costs and value-added are distributed, and where interventions would be most effective to reduce prices. Second, more empirical work is needed on the time and energy costs of meal preparation, especially in biomass-reliant contexts. Meal preparation activities such as washing, chopping, or processing ingredients impose additional time burdens that likely vary by food group. For example, preparing leafy greens or cleaning animal-source foods can be labor- and water-intensive, especially in areas without piped water access. Third, deeper analysis of within-group food preferences could improve understanding of taste, convenience, and aspiration-driven food upgrading. Finally, monitoring and modeling dietary transitions over time will help design anticipatory policy to protect public health as incomes rise and food systems evolve. The findings presented here also point to the need for greater integration of cooking energy and diet quality research, building on existing cookstove and energy transition literature

to assess impacts not only on respiratory health but also on dietary intake and nutritional well-being.

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Chapter 6

Appendices

Consumption and expenditure data

Food consumption data cleaning and analysis

The food consumption module asks one household member to report all food consumed by the household over the past 7 days, both in total and categorized by source: purchased (with price recorded), own-production, or received as gifts or from other sources. It also collects information on the number of days that aggregated food categories were consumed by the household, as well as the number of days and meals eaten by children and adults within the household. Table I shows the number of food items asked about in the questionnaire.

Table I: Food consumption module cleaning

	2010	**2013**	**2016**	**2019**	**2019-20**
Observations	200,756	246,760	353,628	451,276	1,623,628
Unique foods included*	125	124	141	142	142
Specified other foods	45	N/A	97	184	1,292
Unique units included	61	50	68	64	66
Specified other units	32	N/A	164	146	175
Unconverted items					
Missing food composition	672	1,288	1,193	1,630	
	2.32%	3.10%	2.49%	2.55%	

The data cleaning process involves several steps to ensure accuracy and consistency. First, any observation where both the amount and unit are either zero or missing is recoded as missing. If either the amount or unit alone is missing, the record is also recoded as missing. Households without any food consumption data are dropped.

Items classified as "other, specify" are reclassified into standard item codes, as are units. Non-standard unit conversion factors are available for most survey rounds. For the 2010 panel,

I use the 2011 non-standard unit conversion factors for each of Malawi's three regions. For 2013 and 2016, the IHS4 Conversion Factor Database was used, and for the 2019 panel and the IHS5 data, I used the 2020 IHS Conversion Factor database.

Steps:

1. Recode as missing if both the amount and the unit are either zero or missing
2. Recode as missing if either the amount or the unit are missing
3. Drop records with no consumption information
4. Adjust consumption from sources (purchases, own-production, and gifts/other) and total consumption information match.
5. Reclassify foods specified in the "other" categories to standard item codes
6. Reclassify units specified in the "other" categories to standard unit codes
7. Convert all consumption to kilograms.
8. Clean quantities consumed and expenditures to remove extreme values.
9. Energy adjustment: adjusted in the proportion they were reportedly consumed to the point at which household needs equal to consumption; adjust all targets by ratio of total energy consumed to total energy needs
10. Drop households with no reported consumption.

Differences with World Bank consumption aggregate method

- WB winsorizes expenditure for drinking water, utilities (including firewood, electricity, cell phone) at 5/95th percentile of the households' monthly expenditure (not per capita).
- I drop the following non-consumption categories: diesel (211), bicycle spare parts and accessories (216), wages paid to servants (217), cement (408), paint (409), bricks(410), construction timber(411), council rates (412), insurance (health, auto, etc.) (413), losses to theft (value lost) (414), fines or legal fees (415), *lobola* (bridewealth costs) (416), marriage ceremony costs (417), funeral costs, household members (418), funeral costs, non-household members (419), woodpoles, bamboo (420).
- I winsorize higher-level categories at the 1st and 99th percentile by urban region and panel or just urban region.

Diet quality metrics

Global Diet Quality Score

I use energy-adjusted food consumption to generate a household-level Global Diet Quality Score. I make the following assumptions about food classifications:

- Maize grain, normal and bran maize flour, green maize, and boiled or roasted maize are treated as whole grains.
- I treat all milk products in the food list as high fat.
- Meat products that are not specified otherwise are considered "unprocessed" (e.g., pork, mutton).

Mean food group adequacy

The MFGA is based on the HDB (table I).

Table I: Healthy Diet Basket composition

Food group	No. of foods selected	Dietary energy (kcal)	Proportion of energy content
Starchy staples	2	1160	0.498
Oils and fats	1	300	0.129
Vegetables	3	110	0.047
Fruits	2	160	0.069
Legumes nuts and seeds	1	300	0.129
Animal source foods	2	300	0.129
Total	**11**	**2330**	**1.000**

Source: ?Herforth et al. (2022c)

Example diets and their resulting MFGA scores are demonstrated in table II. Example 1 is an example of a uniform deficiency across food groups. In Example 2, 570 calories of sugar-sweetened beverages or other discretionary foods replace starchy staples. In Example 3, 570 calories of discretionary food displaces LNS, and fruits and vegetables (F&V). In example 4, LNS and F&V are displaced by starchy staples rather than discretionary foods.

Mean Adequacy Ratio

MAR is used to measure the nutritional adequacy of an individual's diet by comparing nutrient intake to recommended intakes. I calculate MAR for the household, by generating NAR based on the combined nutrient needs of each household member, based on their age and sex. Intakes are derived by matching each food consumed to its nutrient composition

Table II: Properties of Mean Food Group Adequacy (MFGA) metric, illustrated with examples of dietary patterns

	HDB Target		**Ex 1**		**Ex 2**		**Ex 3**		**Ex 4.**	
Food group	Calories	Deficiency	Calories	Deficiency	Calories	Deficiency	Calories	Deficiency	Calories	Deficiency
Starchy staples	1160	0.000	876	-0.245	590	-0.491	1160	0.000	1730	0.000
Animal source foods	300	0.000	227	-0.245	300	0.000	300	0.000	300	0.000
Oils and fats	300	0.000	227	-0.245	300	0.000	300	0.000	300	0.000
Legumes, nuts, seeds	300	0.000	227	-0.245	300	0.000	0	-1.000	0	-1.000
Fruits	160	0.000	121	-0.245	160	0.000	0	-1.000	0	-1.000
Vegetables	110	0.000	83	-0.245	110	0.000	0	-1.000	0	-1.000
Discretionary	0	0.000	570	-	570	-	570	-	570	-
Total, 6 HDB groups	2330	0.000	1760	-0.245	1760	-0.082	1760	-0.500	2330	-0.500
Mean adequacy (MFGA)	1.000		0.755		0.918		0.500		0.500	
Total intake per day	2330		2330		2330		2330		2330	

using Food Composition Tables Vicent, A et al. (2020); USDA Agricultural Research Service (2016b). MAR is an average of the individual, each of which is capped at 1. I include the following 16 nutrients: carbohydrates, protein, vitamin A, vitamin C, vitamin E, thiamin, riboflavin, niacin, vitamin B6, vitamin B12, calcium, copper, iron, magnesium, phosphorus, and zinc. I exclude nutrients for which there is no Recommended Dietary Allowance (RDA), for which there is only an Adequate Intake, or for which data is not commonly reported in food composition tables.

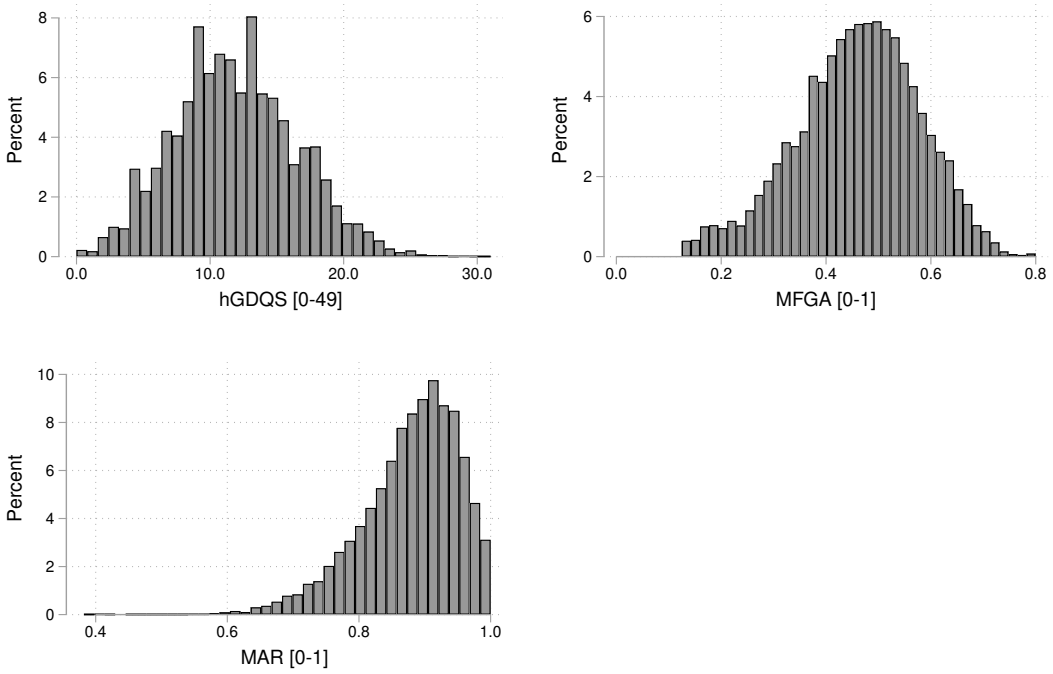


Figure 1: Frequency of diet quality metrics, pooled sample

Notes: ADD NOTE.

Correlation between diet quality metrics

Table III: Pearson correlation coefficients for diet quality metrics

	(1) hGDQS [0-49]	(2) MFGA [0-1]	(3) MAR [0-1]
hGDQS [0-49]	1.000	0.672***	0.469***
MFGA [0-1]	0.672***	1.000	0.610***
MAR [0-1]	0.469***	0.610***	1.000
hGDQS Healthy (hGDQS+)	0.908***	0.599***	0.487***
hGDQS Unhealthy (hGDQS-)	0.409***	0.273***	0.055***
Observations	9295	9295	9295

Note: hGDQS = household Global Diet Quality Score, MFGA = Mean food group adequacy, MAR = Mean Adequacy Ratio.

Nonparametric bivariate relationships by panel

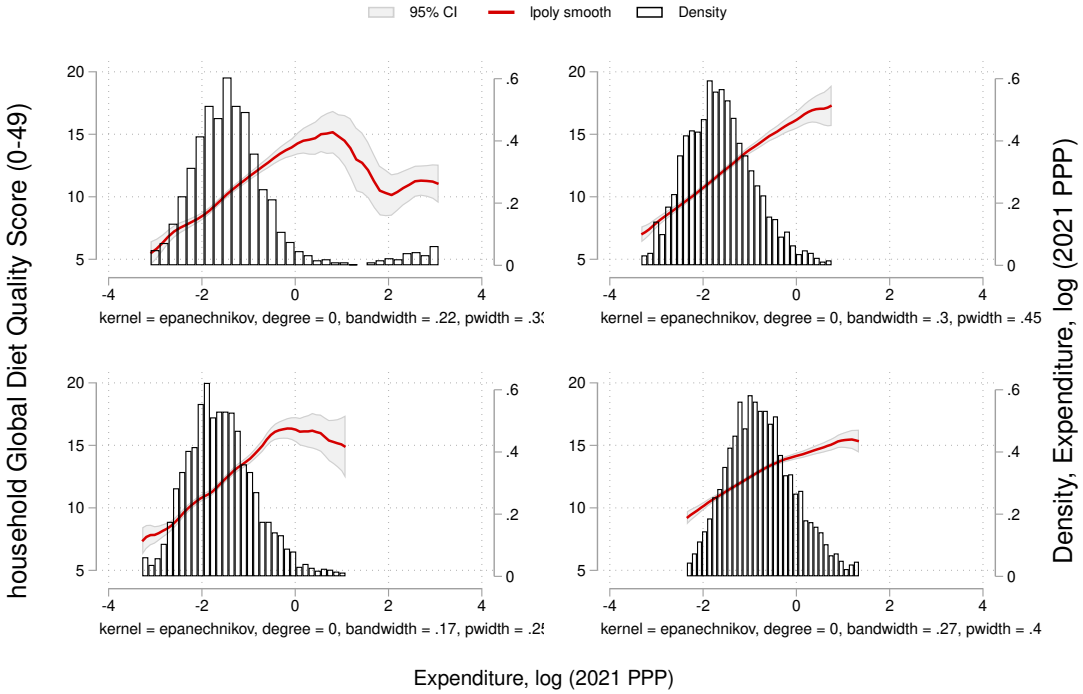


Figure 2: Nonparametric bivariate relationship between hGDQS scores by panel

Notes: Figures show the smoothed values and 95% confidence bands from kernel-weighted local polynomial regression of diet quality outcomes on logged expenditure.Expenditure is in 2021 PPP/AE/day. Expenditure is truncated at percentile 1 and 99 of total expenditure.

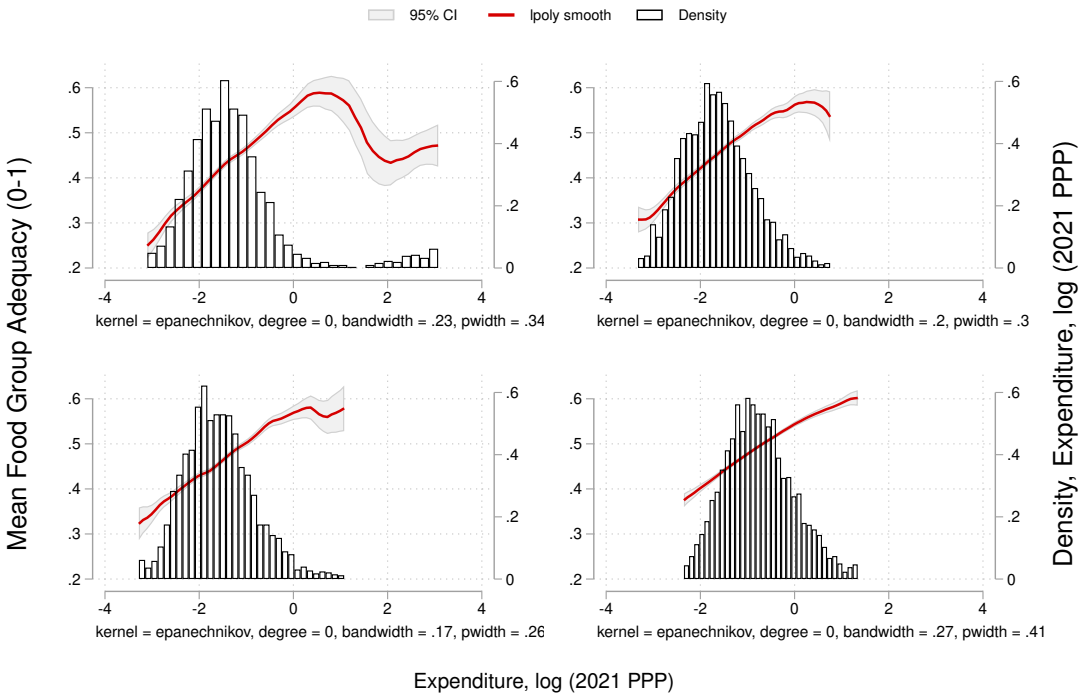


Figure 3: Nonparametric bivariate relationship between MFGA scores by panel

Notes: Figures show the smoothed values and 95% confidence bands from kernel-weighted local polynomial regression of diet quality outcomes on logged expenditure.Expenditure is in 2021 PPP/AE/day. Expenditure is truncated at percentile 1 and 99 of total expenditure.

Full regression specifications

I show OLS and IV specifications with expenditure and expenditure squared (IV, V, VI).

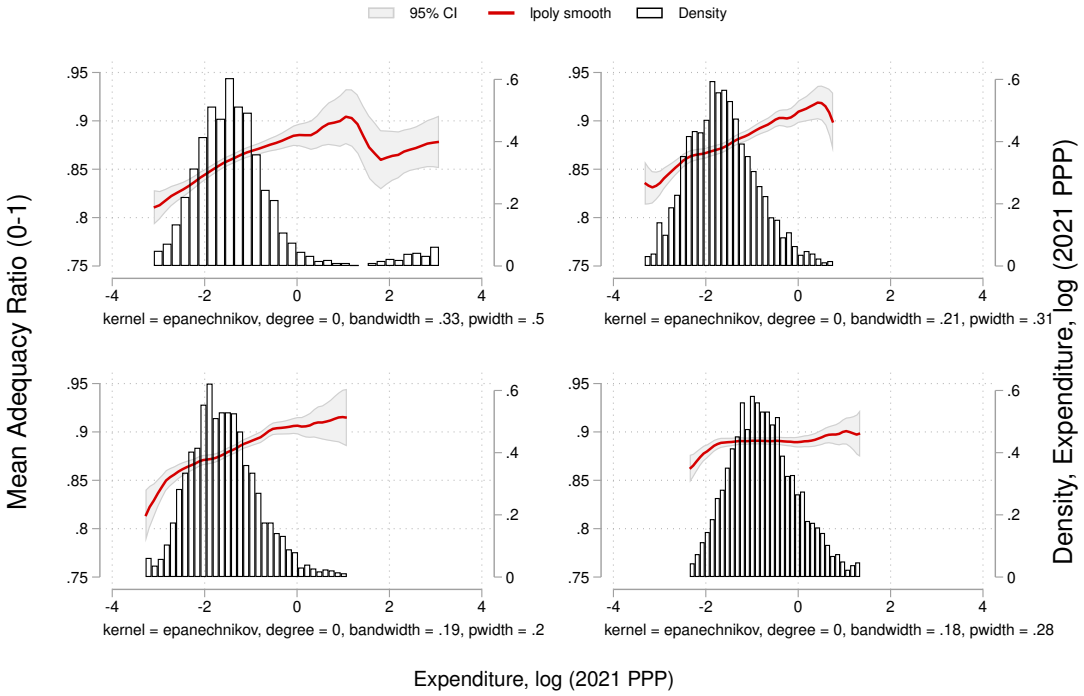


Figure 4: Nonparametric bivariate relationship between MAR scores by panel

Notes: Figures show the smoothed values and 95% confidence bands from kernel-weighted local polynomial regression of diet quality outcomes on logged expenditure.Expenditure is in 2021 PPP/AE/day. Expenditure is truncated at percentile 1 and 99 of total expenditure.

Table IV: Full OLS and 2SLS specifications with panel data, hGDQS

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) 2SLS	(8) 2SLS	(9) 2SLS	(10) 2SLS Pref
Expenditure	0.000**	0.003***	0.002***							
	(0.000)	(0.000)	(0.000)							
Expenditure × Expenditure		-0.000***	-0.000***							
		(0.000)	(0.000)							
Head age (years)			-0.001		-0.006	-0.005		-0.010		-0.008**
			(0.007)		(0.007)	(0.004)		(0.007)		(0.004)
Head educ. (years complete)			0.140***		0.061**	0.068***		-0.018		0.005
			(0.025)		(0.025)	(0.016)		(0.031)		(0.020)
Rural (0/1)			-1.433***		-0.987***	-0.944***		-0.479		-0.623***
			(0.300)		(0.291)	(0.206)		(0.318)		(0.214)
Centre			-0.336		-0.187	-0.048		-0.073		0.063
			(0.270)		(0.255)	(0.123)		(0.262)		(0.130)
Children (0-5)			0.135		0.258**	0.196**		0.377***		0.329***
			(0.124)		(0.119)	(0.077)		(0.126)		(0.081)
Male children (5-15)			0.016		0.137	0.203***		0.249**		0.304***
			(0.097)		(0.092)	(0.065)		(0.102)		(0.070)
Female children (5-15)			-0.004		0.087	0.161**		0.169		0.238***
			(0.104)		(0.101)	(0.064)		(0.106)		(0.067)
Male working age (15-64)			0.114		0.219**	0.328***		0.305***		0.445***
			(0.111)		(0.105)	(0.074)		(0.109)		(0.075)
Female working age (15-64)			0.207*		0.219**	0.227***		0.227**		0.224***
			(0.109)		(0.102)	(0.070)		(0.104)		(0.071)
Dist. (km) to nearest population center (20k+)			-0.003		-0.002	-0.003		-0.001		-0.001
			(0.007)		(0.007)	(0.004)		(0.007)		(0.004)
Dist. (km) to nearest ADMARC depot			-0.010		0.007	-0.017		0.024		-0.008
			(0.019)		(0.017)	(0.011)		(0.018)		(0.011)
Dist. (km) to nearest district market			0.011**		0.008*	0.009***		0.005		0.008**
			(0.004)		(0.004)	(0.003)		(0.004)		(0.003)
Weather-related shocks experienced in last 12 months			0.193*		0.265***	0.141**		0.328***		0.213***
			(0.102)		(0.097)	(0.062)		(0.104)		(0.066)
Received free maize (0/1)			0.992***		1.125***	1.120***		1.217***		1.215***
			(0.307)		(0.292)	(0.197)		(0.303)		(0.196)
Received free food other than maize (0/1)			0.675		0.545	-0.169		0.399		-0.080
			(0.549)		(0.522)	(0.376)		(0.544)		(0.366)
Expenditure, log				1.850***	1.746***	1.821***	3.262***	3.122***	3.292***	2.947***
				(0.115)	(0.125)	(0.111)	(0.209)	(0.347)	(0.166)	(0.245)
Constant	11.255***	10.906***	10.601***	2.910***	2.675***	2.324***				
	(0.026)	(0.057)	(0.580)	(0.523)	(0.829)	(0.619)				
Mean	11.32	11.32	11.32	11.32	11.32	11.49	11.32	11.32	11.48	11.49
Survey weights	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Household	Household	Household	Household	Household	No	Household	Household	No	No
Time FE	Panel	Panel	Panel	Panel	Panel	Panel	Panel	Panel	Panel	Panel
Controls	No	No	Lasso	No	Lasso	Lasso	No	Lasso	No	Lasso

Table V: Full OLS and 2SLS specifications with panel data, MFGA

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) 2SLS	(8) 2SLS	(9) 2SLS	(10) 2SLS Pref
Expenditure	0.000***	0.000***	0.000***							
	(0.000)	(0.000)	(0.000)							
Expenditure × Expenditure		-0.000***	-0.000***							
		(0.000)	(0.000)							
Head age (years)			-0.000		-0.000*	-0.000***		-0.000**		-0.001***
			(0.000)		(0.000)	(0.000)		(0.000)		(0.000)
Head educ. (years complete)			0.005***		0.003***	0.003***		0.001		0.001**
			(0.001)		(0.001)	(0.000)		(0.001)		(0.001)
Rural (0/1)			-0.051***		-0.040***	-0.033***		-0.021***		-0.021***
			(0.007)		(0.007)	(0.005)		(0.008)		(0.005)
Centre			-0.020***		-0.016***	-0.010***		-0.012*		-0.006*
			(0.007)		(0.006)	(0.003)		(0.006)		(0.003)
Children (0-5)			-0.006*		-0.003	-0.004*		0.002		0.001
			(0.003)		(0.003)	(0.002)		(0.003)		(0.002)
Male children (5-15)			-0.005*		-0.002	-0.001		0.002		0.003
			(0.003)		(0.002)	(0.002)		(0.003)		(0.002)
Female children (5-15)			-0.003		-0.001	-0.001		0.002		0.002
			(0.003)		(0.003)	(0.002)		(0.003)		(0.002)
Male working age (15-64)			-0.004		-0.002	0.004**		0.002		0.008***
			(0.003)		(0.003)	(0.002)		(0.003)		(0.002)
Female working age (15-64)			0.005**		0.006**	0.004**		0.006**		0.004**
			(0.003)		(0.003)	(0.002)		(0.003)		(0.002)
Dist. (km) to nearest population center (20k+)			-0.000		-0.000	-0.000***		-0.000		-0.000**
			(0.000)		(0.000)	(0.000)		(0.000)		(0.000)
Dist. (km) to nearest ADMARC depot			-0.001**		-0.001	-0.001*		-0.000		-0.000
			(0.000)		(0.000)	(0.000)		(0.000)		(0.000)
Dist. (km) to nearest district market			0.000**		0.000**	0.000***		0.000		0.000**
			(0.000)		(0.000)	(0.000)		(0.000)		(0.000)
Weather-related shocks experienced in last 12 months			-0.001		0.001	0.001		0.003		0.003**
			(0.002)		(0.002)	(0.001)		(0.003)		(0.002)
Received free maize (0/1)			0.018**		0.021***	0.021***		0.024***		0.024***
			(0.008)		(0.008)	(0.005)		(0.008)		(0.005)
Received free food other than maize (0/1)			-0.012		-0.015	-0.016*		-0.020		-0.012
			(0.013)		(0.013)	(0.009)		(0.015)		(0.010)
Expenditure, log				0.048***	0.039***	0.046***	0.103***	0.090***	0.107***	0.087***
				(0.003)	(0.003)	(0.003)	(0.005)	(0.008)	(0.004)	(0.006)
Constant	0.439***	0.430***	0.472***	0.221***	0.292***	0.261***				
	(0.001)	(0.002)	(0.013)	(0.014)	(0.020)	(0.016)				
Mean	0.44	0.44	0.44	0.44	0.44	0.45	0.44	0.44	0.45	0.45
Survey weights	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Household	Household	Household	Household	Household	No	Household	Household	No	No
Time FE	Panel	Panel	Panel	Panel	Panel	Panel	Panel	Panel	Panel	Panel
Controls	No	No	Lasso	No	Lasso	Lasso	No	Lasso	No	Lasso
N	6092	6092	5880	6092	5880	9035	6091	5879	9270	9034
F-Stat	7.04	21.31	24.73	242.22	37.26	88.23	388.76	31.44	732.66	74.18
Sanderson-Windmeijer F-stat							655.80	232.91	1264.66	575.87
Kleibergen-Paap Wald F-Stat							655.80	232.91	1264.66	575.87
Cragg-Donald Wald F-stat							1183.13	459.72	2085.26	884.43
Stock-Wright LM S-stat							213.23	112.68	459.90	194.05
Kleibergen-Paap rk LM stat							254.39	161.63	394.93	324.95

Note: hGDQS = household Global Diet Quality Score, MFGA = Mean food group adequacy, MAR = Mean Adequacy Ratio.

Table VI: Full OLS and 2SLS specifications with panel data, MAR

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) 2SLS	(8) 2SLS	(9) 2SLS	(10) 2SLS Pref
Expenditure	0.000	0.000***	0.000**							
	(0.000)	(0.000)	(0.000)							
Expenditure × Expenditure		-0.000***	-0.000**							
		(0.000)	(0.000)							
Head age (years)			-0.000***		-0.000***	-0.001***		-0.001***		-0.001***
			(0.000)		(0.000)	(0.000)		(0.000)		(0.000)
Head educ. (years complete)			0.001***		0.001	0.001***		0.001		0.000
			(0.000)		(0.000)	(0.000)		(0.001)		(0.000)
Rural (0/1)			-0.026***		-0.024***	-0.011***		-0.023***		-0.009**
			(0.005)		(0.005)	(0.003)		(0.005)		(0.004)
Centre			-0.005		-0.005	-0.002		-0.004		-0.001
			(0.005)		(0.004)	(0.002)		(0.005)		(0.002)
Children (0-5)			-0.001		-0.000	-0.001		-0.000		0.000
			(0.002)		(0.002)	(0.001)		(0.002)		(0.002)
Male children (5-15)			0.002		0.002	0.005***		0.003		0.006***
			(0.002)		(0.002)	(0.001)		(0.002)		(0.001)
Female children (5-15)			-0.002		-0.001	-0.001		-0.001		-0.000
			(0.002)		(0.002)	(0.001)		(0.002)		(0.001)
Male working age (15-64)			0.008***		0.009***	0.012***		0.009***		0.013***
			(0.002)		(0.002)	(0.001)		(0.002)		(0.001)
Female working age (15-64)			0.001		0.001	-0.000		0.001		-0.001
			(0.002)		(0.002)	(0.002)		(0.002)		(0.002)
Dist. (km) to nearest population center (20k+)			0.000		0.000	-0.000		0.000		-0.000
			(0.000)		(0.000)	(0.000)		(0.000)		(0.000)
Dist. (km) to nearest ADMARC depot			0.000		0.000	0.000		0.000		0.000
			(0.000)		(0.000)	(0.000)		(0.000)		(0.000)
Dist. (km) to nearest district market			0.000***		0.000***	0.000**		0.000***		0.000**
			(0.000)		(0.000)	(0.000)		(0.000)		(0.000)
Weather-related shocks experienced in last 12 months			0.002		0.002	0.001		0.002		0.002
			(0.002)		(0.002)	(0.001)		(0.002)		(0.001)
Received free maize (0/1)			0.015***		0.016***	0.010***		0.016***		0.011***
			(0.005)		(0.005)	(0.003)		(0.005)		(0.003)
Received free food other than maize (0/1)			0.005		0.004	-0.012		0.004		-0.011
			(0.012)		(0.012)	(0.008)		(0.012)		(0.008)
Expenditure, log				0.013***	0.011***	0.010***	0.029***	0.014**	0.030***	0.020***
				(0.002)	(0.002)	(0.002)	(0.004)	(0.006)	(0.003)	(0.004)
Constant	0.868***	0.865***	0.878***	0.808***	0.829***	0.836***				
	(0.001)	(0.001)	(0.010)	(0.009)	(0.014)	(0.010)				
Mean	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87
Survey weights	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Household	Household	Household	Household	Household	No	Household	Household	No	No
Time FE	Panel	Panel	Panel	Panel	Panel	Panel	Panel	Panel	Panel	Panel
Controls	No	No	Lasso	No	Lasso	Lasso	No	Lasso	No	Lasso
N	6092	6092	5880	6092	5880	9035	6091	5879	9270	9034
F-Stat	1.04	7.81	7.93	50.09	10.22	23.18	58.81	8.83	119.59	19.87
Sanderson-Windmeijer F-stat							655.80	232.91	1264.66	575.87
Kleibergen-Paap Wald F-Stat							655.80	232.91	1264.66	575.87
Cragg-Donald Wald F-stat							1183.13	459.72	2085.26	884.43
Stock-Wright LM S-stat							52.60	5.36	131.84	22.58
Kleibergen-Paap rk LM stat							254.39	161.63	394.93	324.95

Note: hGDQS = household Global Diet Quality Score, MFGA = Mean food group adequacy, MAR = Mean Adequacy Ratio.

Our preferred specification uses the panel data but does not include the household fixed effects, given the large number of singleton households in the unbalanced panel. Analysis of singleton households that would otherwise be dropped suggests that they are statistically significantly different from other households in the sample in important characteristics (table 2.4).

Table VII: Full 2SLS specification and alternate instruments, hGDQS

	(1) OLS	(2) OLS	(3) 2SLS first stage	(4) 2SLS	(5) 2SLS first stage	(6) 2SLS	(7) 2SLS first stage	(8) 2SLS
Expenditure, log	1.903***	1.821***		2.947***		2.822***		1.932***
	(0.095)	(0.111)		(0.245)		(0.242)		(0.630)
Head age (years)		-0.005	0.000	-0.008**	0.000	-0.008*	0.003***	-0.005
		(0.004)	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)	(0.005)
Head educ. (years complete)		0.068***	0.027***	0.005	0.027***	0.012	0.054***	0.061
		(0.016)	(0.003)	(0.020)	(0.003)	(0.020)	(0.003)	(0.038)
Rural (0/1)		-0.944***	-0.062*	-0.623***	-0.055	-0.659***	-0.146***	-0.913***
		(0.206)	(0.034)	(0.214)	(0.034)	(0.213)	(0.041)	(0.286)
Centre		-0.048	-0.060***	0.063	-0.059**	0.051	-0.057**	-0.037
		(0.123)	(0.023)	(0.130)	(0.023)	(0.129)	(0.024)	(0.132)
Children (0-5)		0.196**	-0.105***	0.329***	-0.104***	0.314***	-0.118***	0.209**
		(0.077)	(0.015)	(0.081)	(0.015)	(0.081)	(0.016)	(0.106)
Male children (5-15)		0.203***	-0.086***	0.304***	-0.086***	0.293***	-0.084***	0.213**
		(0.065)	(0.014)	(0.070)	(0.014)	(0.070)	(0.014)	(0.083)
Female children (5-15)		0.161**	-0.069***	0.238***	-0.068***	0.230***	-0.062***	0.169**
		(0.064)	(0.013)	(0.067)	(0.013)	(0.066)	(0.013)	(0.072)
Male working age (15-64)		0.328***	-0.131***	0.445***	-0.128***	0.432***	-0.106***	0.340***
		(0.074)	(0.012)	(0.075)	(0.012)	(0.075)	(0.013)	(0.103)
Female working age (15-64)		0.227***	-0.041***	0.224***	-0.041***	0.224***	0.003	0.227***
		(0.070)	(0.012)	(0.071)	(0.012)	(0.070)	(0.013)	(0.070)
Dist. (km) to nearest population center (20k+)		-0.003	-0.002***	-0.001	-0.002***	-0.001	-0.002***	-0.003
		(0.004)	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)	(0.004)
Dist. (km) to nearest ADMARC depot		-0.017	-0.007***	-0.008	-0.007***	-0.009	-0.007***	-0.016
		(0.011)	(0.002)	(0.011)	(0.002)	(0.011)	(0.002)	(0.013)
Dist. (km) to nearest district market		0.009***	0.001**	0.008**	0.001**	0.008***	0.001**	0.009***
		(0.003)	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)	(0.003)
Weather-related shocks experienced in last 12 months		0.141**	-0.050***	0.213***	-0.050***	0.205***	-0.043***	0.148**
		(0.062)	(0.011)	(0.066)	(0.011)	(0.066)	(0.012)	(0.069)
Received free maize (0/1)		1.120***	-0.047	1.215***	-0.048	1.205***	-0.068**	1.130***
		(0.197)	(0.032)	(0.196)	(0.032)	(0.196)	(0.034)	(0.202)
Received free food other than maize (0/1)		-0.169	-0.016	-0.080	-0.021	-0.090	-0.066	-0.160
		(0.376)	(0.063)	(0.366)	(0.064)	(0.366)	(0.058)	(0.377)
Weighted combination of asset components (3)			0.204***					
			(0.008)					
Combined asset index					0.209***			
					(0.009)			
Median non-food expenditure							0.005***	
							(0.001)	
Constant	2.747***	2.324***						
	(0.427)	(0.619)						
Mean	11.48	11.49		11.49		11.49		11.49
Survey weights	Yes	Yes		Yes		Yes		Yes
Household FE	No	No		No		No		No
Time FE	Panel	Panel		Panel		Panel		Panel
Control	No	Yes		Yes		Yes		Yes
N	9295.00	9059.00	9058.00	9058.00	9058.00	9058.00	9059.00	9059.00
Sanderson-Windmeijer F-stat			584.14		575.26		58.44	
KP Wald F-Stat			584.14		575.26		58.44	
Cragg-Donald Wald F-stat			895.47		894.24		216.74	
Stock-Wright LM S-stat			141.22		130.95		12.01	
Kleibergen-Paap rk LM stat			320.00		310.32		58.07	

Note: hGDQS = household Global Diet Quality Score, MFGA = Mean food group adequacy, MAR = Mean Adequacy Ratio.

Table VIII: Full 2SLS specification and alternate instruments, MFGA

	(1) OLS	(2) OLS	(3) 2SLS first stage	(4) 2SLS	(5) 2SLS first stage	(6) 2SLS	(7) 2SLS first stage	(8) 2SLS
Expenditure, log	0.057***	0.046***		0.087***		0.085***		0.072***
	(0.003)	(0.003)		(0.006)		(0.006)		(0.014)
Head age (years)		-0.000***	0.000	-0.001***	0.000	-0.001***	0.003***	-0.000***
		(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Head educ. (years complete)		0.003***	0.027***	0.001**	0.027***	0.001**	0.054***	0.002**
		(0.000)	(0.003)	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)
Rural (0/1)		-0.033***	-0.059*	-0.021***	-0.053	-0.022***	-0.144***	-0.025***
		(0.005)	(0.034)	(0.005)	(0.034)	(0.005)	(0.041)	(0.007)
Centre		-0.010***	-0.061***	-0.006*	-0.059***	-0.006*	-0.057**	-0.007**
		(0.003)	(0.023)	(0.003)	(0.023)	(0.003)	(0.024)	(0.003)
Children (0-5)		-0.004*	-0.105***	0.001	-0.104***	0.001	-0.117***	-0.001
		(0.002)	(0.015)	(0.002)	(0.015)	(0.002)	(0.016)	(0.003)
Male children (5-15)		-0.001	-0.086***	0.003	-0.085***	0.003	-0.083***	0.002
		(0.002)	(0.014)	(0.002)	(0.014)	(0.002)	(0.014)	(0.002)
Female children (5-15)		-0.001	-0.069***	0.002	-0.068***	0.002	-0.062***	0.001
		(0.002)	(0.013)	(0.002)	(0.013)	(0.002)	(0.013)	(0.002)
Male working age (15-64)		0.004**	-0.131***	0.008***	-0.128***	0.008***	-0.106***	0.006***
		(0.002)	(0.012)	(0.002)	(0.012)	(0.002)	(0.013)	(0.002)
Female working age (15-64)		0.004**	-0.041***	0.004**	-0.041***	0.004**	0.004	0.004**
		(0.002)	(0.012)	(0.002)	(0.012)	(0.002)	(0.013)	(0.002)
Dist. (km) to nearest population center (20k+)		-0.000***	-0.002***	-0.000**	-0.002***	-0.000**	-0.002***	-0.000**
		(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Dist. (km) to nearest ADMARC depot		-0.001*	-0.007***	-0.000	-0.007***	-0.000	-0.008***	-0.000
		(0.000)	(0.002)	(0.000)	(0.002)	(0.000)	(0.002)	(0.000)
Dist. (km) to nearest district market		0.000***	0.001**	0.000**	0.001**	0.000***	0.001**	0.000***
		(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Weather-related shocks experienced in last 12 months		0.001	-0.050***	0.003**	-0.050***	0.003**	-0.043***	0.002
		(0.001)	(0.011)	(0.002)	(0.011)	(0.002)	(0.012)	(0.002)
Received free maize (0/1)		0.021***	-0.046	0.024***	-0.047	0.024***	-0.067**	0.023***
		(0.005)	(0.032)	(0.005)	(0.032)	(0.005)	(0.034)	(0.005)
Received free food other than maize (0/1)		-0.016*	-0.015	-0.012	-0.020	-0.013	-0.065	-0.014
		(0.009)	(0.063)	(0.010)	(0.064)	(0.010)	(0.058)	(0.009)
Weighted combination of asset components (3)			0.204***					
			(0.009)					
Combined asset index					0.209***			
					(0.009)			
Median non-food expenditure							0.005***	
							(0.001)	
Constant	0.186***	0.261***						
	(0.013)	(0.016)						
Mean	0.45	0.45		0.45		0.45		0.45
Survey weights	Yes	Yes		Yes		Yes		Yes
Household FE	No	No		No		No		No
Time FE	Panel	Panel		Panel		Panel		Panel
Control	No	Yes		Yes		Yes		Yes
N	9271.00	9035.00	9034.00	9034.00	9034.00	9034.00	9035.00	9035.00
Sanderson-Windmeijer F-stat			575.87		566.29		58.47	
KP Wald F-Stat			575.87		566.29		58.47	
Cragg-Donald Wald F-stat			884.43		882.57		213.67	
Stock-Wright LM S-stat			194.05		184.11		32.87	
Kleibergen-Paap rk LM stat			324.95		315.12		57.13	

Note: hGDQS = household Global Diet Quality Score, MFGA = Mean food group adequacy, MAR = Mean Adequacy Ratio.

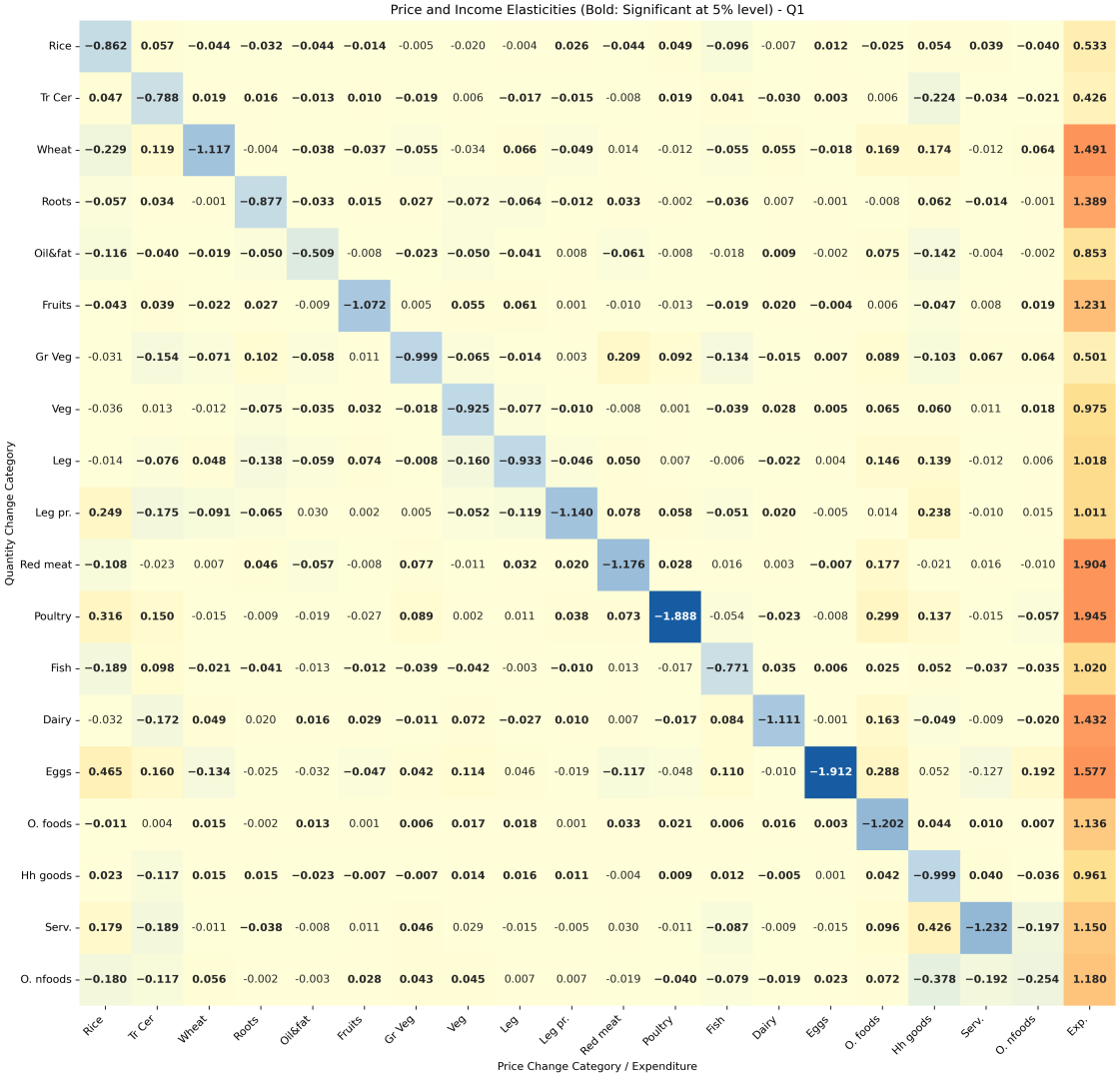
Table IX: Full 2SLS specification and alternate instruments, MAR

	(1) OLS	(2) OLS	(3) 2SLS first stage	(4) 2SLS	(5) 2SLS first stage	(6) 2SLS	(7) 2SLS first stage	(8) 2SLS
Expenditure, log	0.012***	0.010***		0.020***		0.018***		0.020**
	(0.001)	(0.002)		(0.004)		(0.004)		(0.010)
Head age (years)		-0.001***	0.000	-0.001***	0.000	-0.001***	0.003***	-0.001***
		(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Head educ. (years complete)		0.001***	0.027***	0.000	0.027***	0.000	0.054***	0.000
		(0.000)	(0.003)	(0.000)	(0.003)	(0.000)	(0.003)	(0.001)
Rural (0/1)		-0.011***	-0.059*	-0.009**	-0.053	-0.009**	-0.144***	-0.009*
		(0.003)	(0.034)	(0.004)	(0.034)	(0.004)	(0.041)	(0.005)
Centre		-0.002	-0.061***	-0.001	-0.059***	-0.001	-0.057**	-0.001
		(0.002)	(0.023)	(0.002)	(0.023)	(0.002)	(0.024)	(0.003)
Children (0-5)		-0.001	-0.105***	0.000	-0.104***	0.000	-0.117***	0.000
		(0.001)	(0.015)	(0.002)	(0.015)	(0.002)	(0.016)	(0.002)
Male children (5-15)		0.005***	-0.086***	0.006***	-0.085***	0.005***	-0.083***	0.005***
		(0.001)	(0.014)	(0.001)	(0.014)	(0.001)	(0.014)	(0.001)
Female children (5-15)		-0.001	-0.069***	-0.000	-0.068***	-0.001	-0.062***	-0.000
		(0.001)	(0.013)	(0.001)	(0.013)	(0.001)	(0.013)	(0.001)
Male working age (15-64)		0.012***	-0.131***	0.013***	-0.128***	0.013***	-0.106***	0.013***
		(0.001)	(0.012)	(0.001)	(0.012)	(0.001)	(0.013)	(0.002)
Female working age (15-64)		-0.000	-0.041***	-0.001	-0.041***	-0.001	0.004	-0.001
		(0.002)	(0.012)	(0.002)	(0.012)	(0.002)	(0.013)	(0.002)
Dist. (km) to nearest population center (20k+)		-0.000	-0.002***	-0.000	-0.002***	-0.000	-0.002***	-0.000
		(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Dist. (km) to nearest ADMARC depot		0.000	-0.007***	0.000	-0.007***	0.000	-0.008***	0.000
		(0.000)	(0.002)	(0.000)	(0.002)	(0.000)	(0.002)	(0.000)
Dist. (km) to nearest district market		0.000**	0.001**	0.000**	0.001**	0.000**	0.001**	0.000**
		(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Weather-related shocks experienced in last 12 months		0.001	-0.050***	0.002	-0.050***	0.002	-0.043***	0.002
		(0.001)	(0.011)	(0.001)	(0.011)	(0.001)	(0.012)	(0.001)
Received free maize (0/1)		0.010***	-0.046	0.011***	-0.047	0.011***	-0.067**	0.011***
		(0.003)	(0.032)	(0.003)	(0.032)	(0.003)	(0.034)	(0.004)
Received free food other than maize (0/1)		-0.012	-0.015	-0.011	-0.020	-0.011	-0.065	-0.011
		(0.008)	(0.063)	(0.008)	(0.064)	(0.008)	(0.058)	(0.008)
Weighted combination of asset components (3)			0.204***					
			(0.009)					
Combined asset index					0.209***			
					(0.009)			
Median non-food expenditure							0.005***	
							(0.001)	
Constant	0.816***	0.836***						
	(0.007)	(0.010)						
Mean	0.87	0.87		0.87		0.87		0.87
Survey weights	Yes	Yes		Yes		Yes		Yes
Household FE	No	No		No		No		No
Time FE	Panel	Panel		Panel		Panel		Panel
Control	No	Yes		Yes		Yes		Yes
N	9271.00	9035.00	9034.00	9034.00	9034.00	9034.00	9035.00	9035.00
Sanderson-Windmeijer F-stat			575.87		566.29		58.47	
KP Wald F-Stat			575.87		566.29		58.47	
Cragg-Donald Wald F-stat			884.43		882.57		213.67	
Stock-Wright LM S-stat			22.58		17.79		4.64	
Kleibergen-Paap rk LM stat			324.95		315.12		57.13	

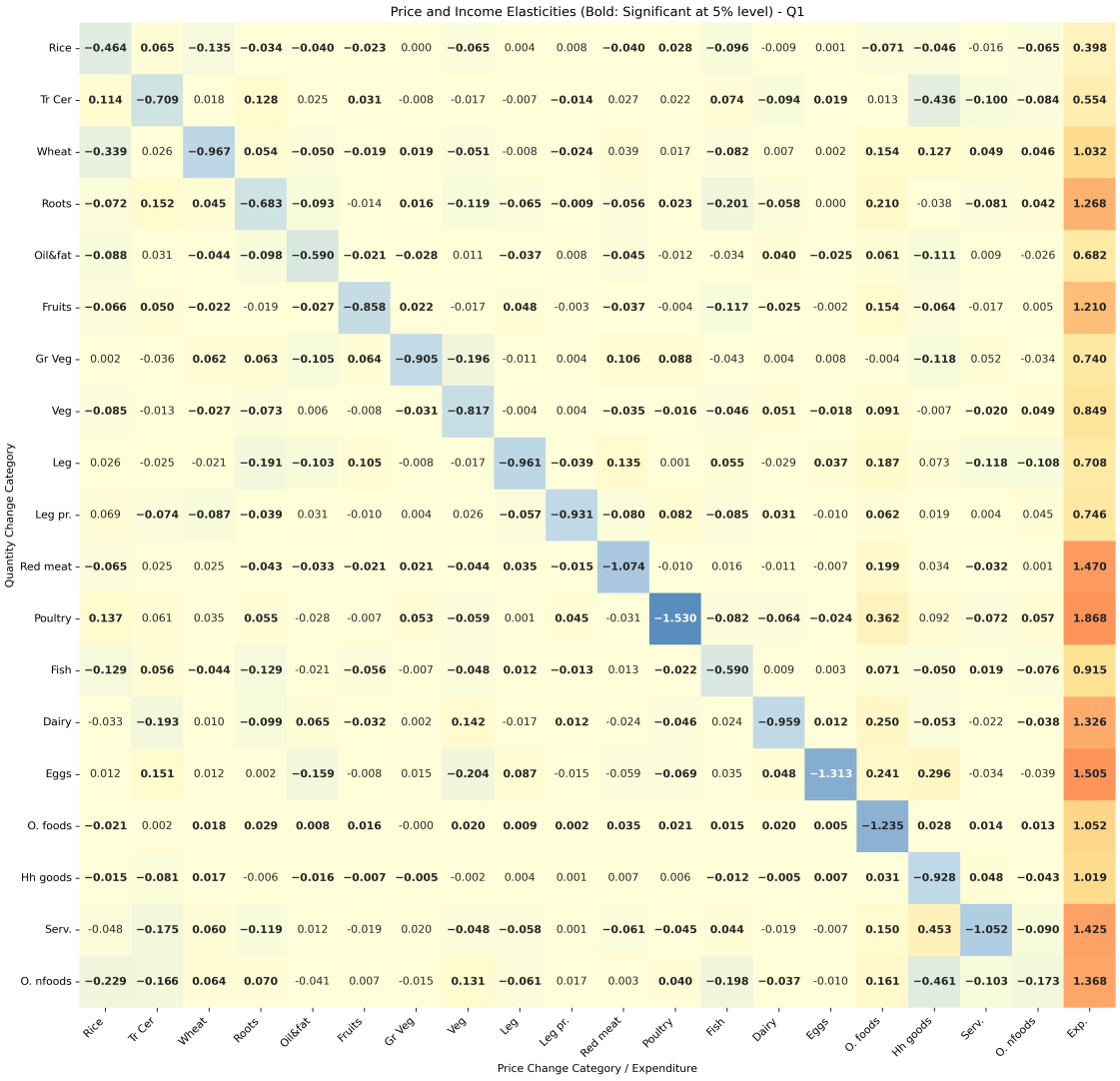
Note: hGDQS = household Global Diet Quality Score, MFGA = Mean food group adequacy, MAR = Mean Adequacy Ratio.

Income and price elasticities controlling for level 1 geographic unit fixed effects

Figure 5: Price and Income Elasticities

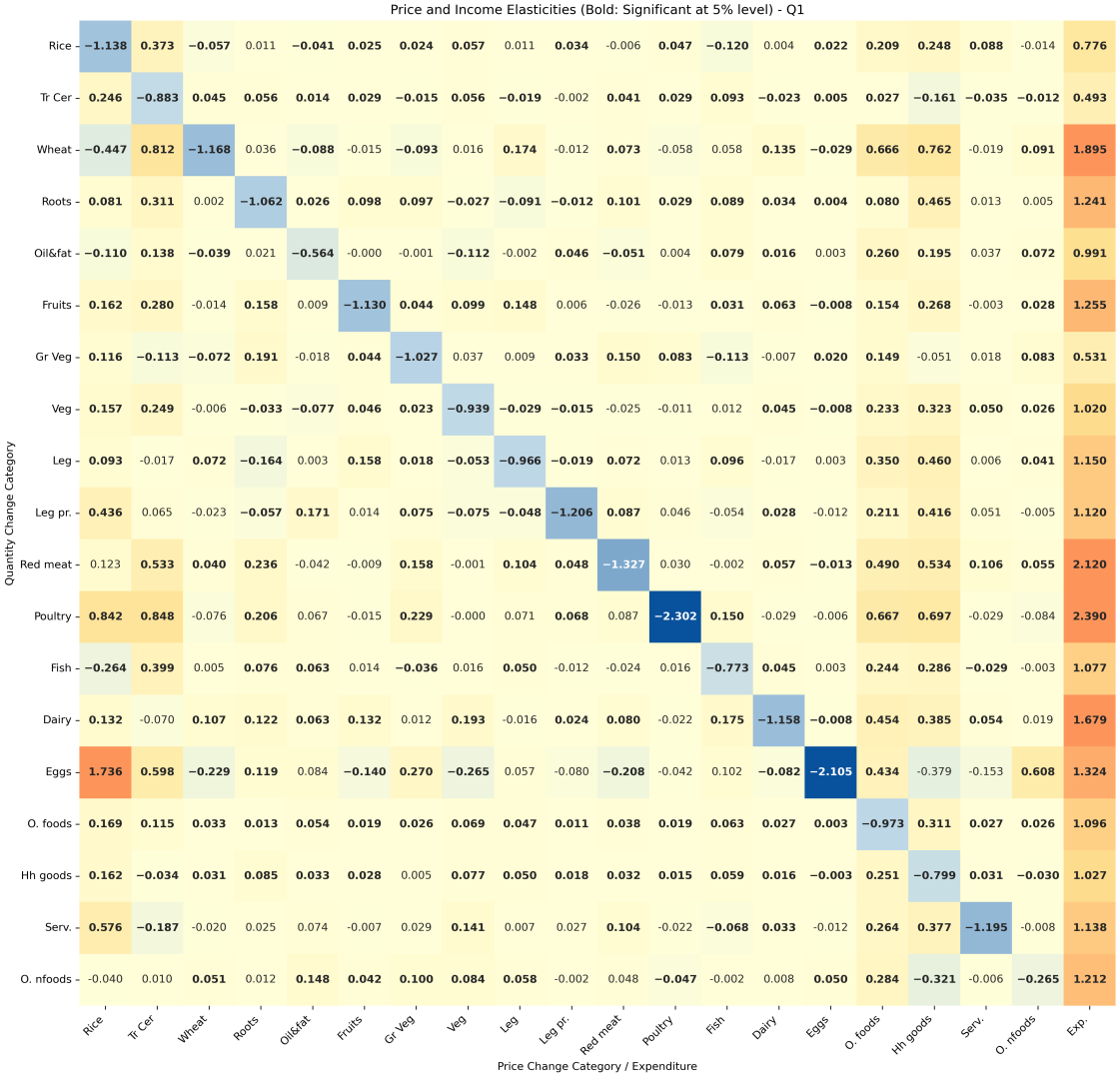


(a) Rural areas

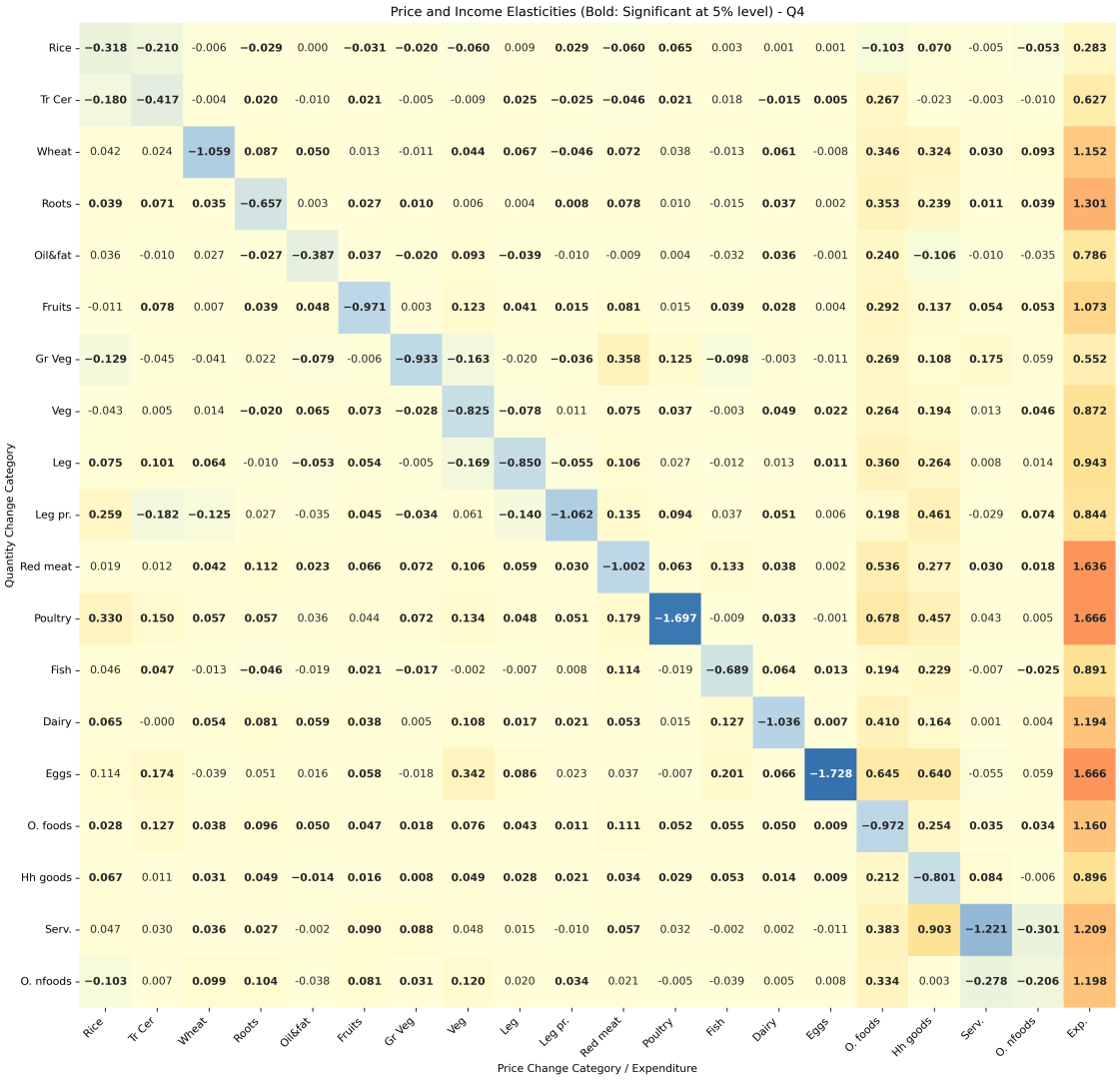


(b) Urban areas

Figure 6: Compensated Price and Income Elasticities, Rural

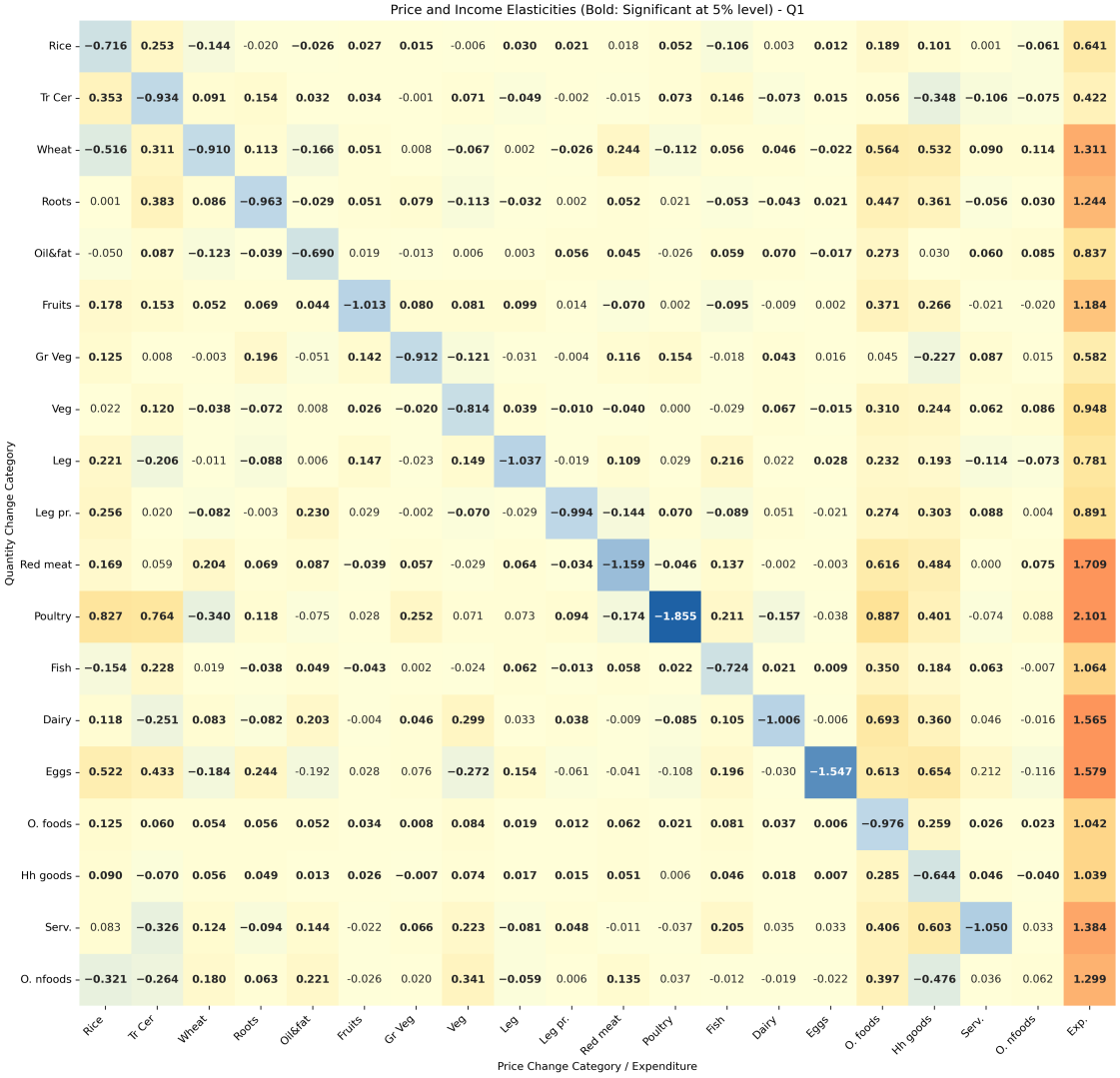


(a) Expenditure Quartile Q1

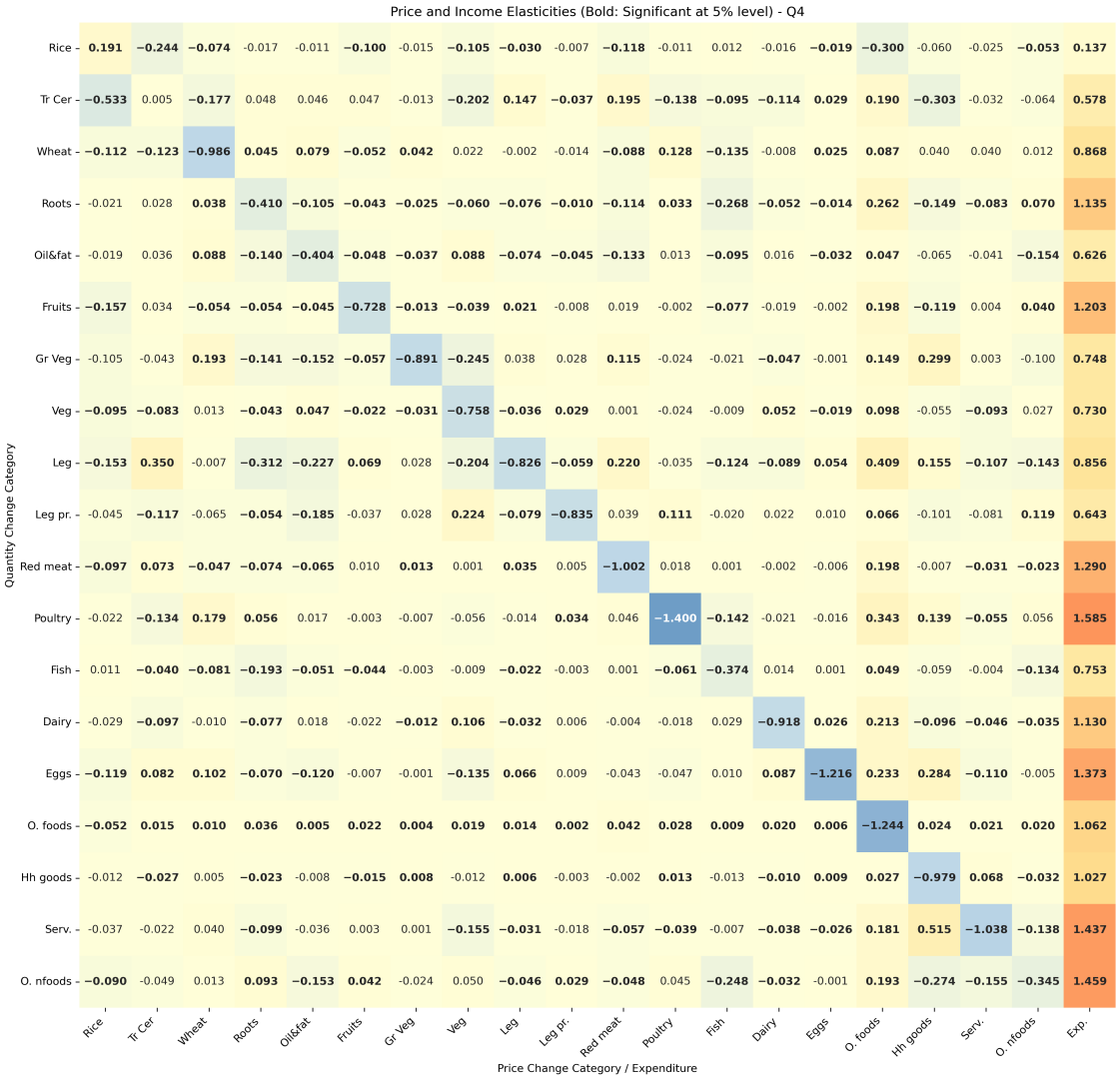


(b) Expenditure Quartile Q4

Figure 7: Compensated Price and Income Elasticities, Urban



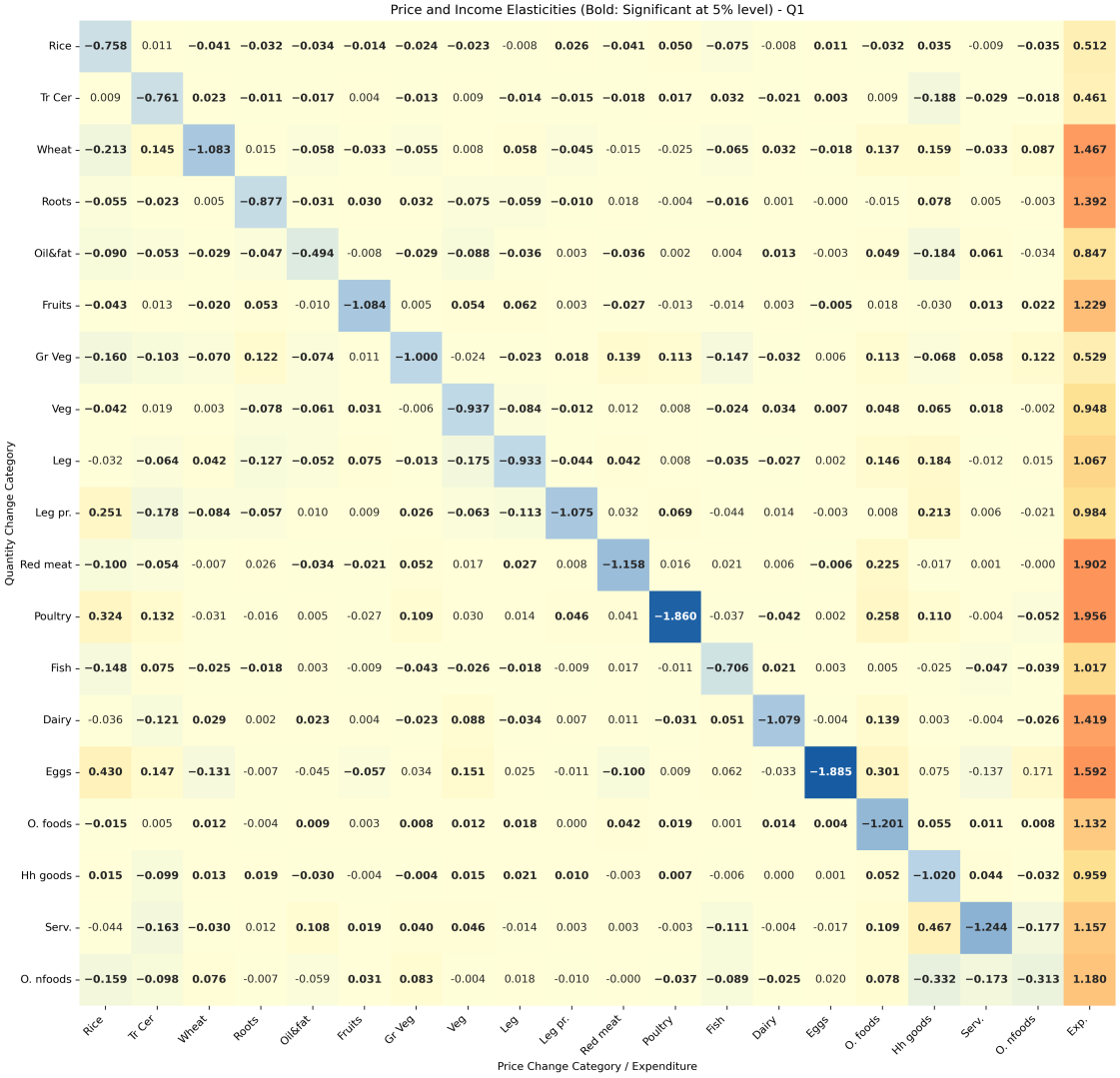
(a) Expenditure Quartile Q1



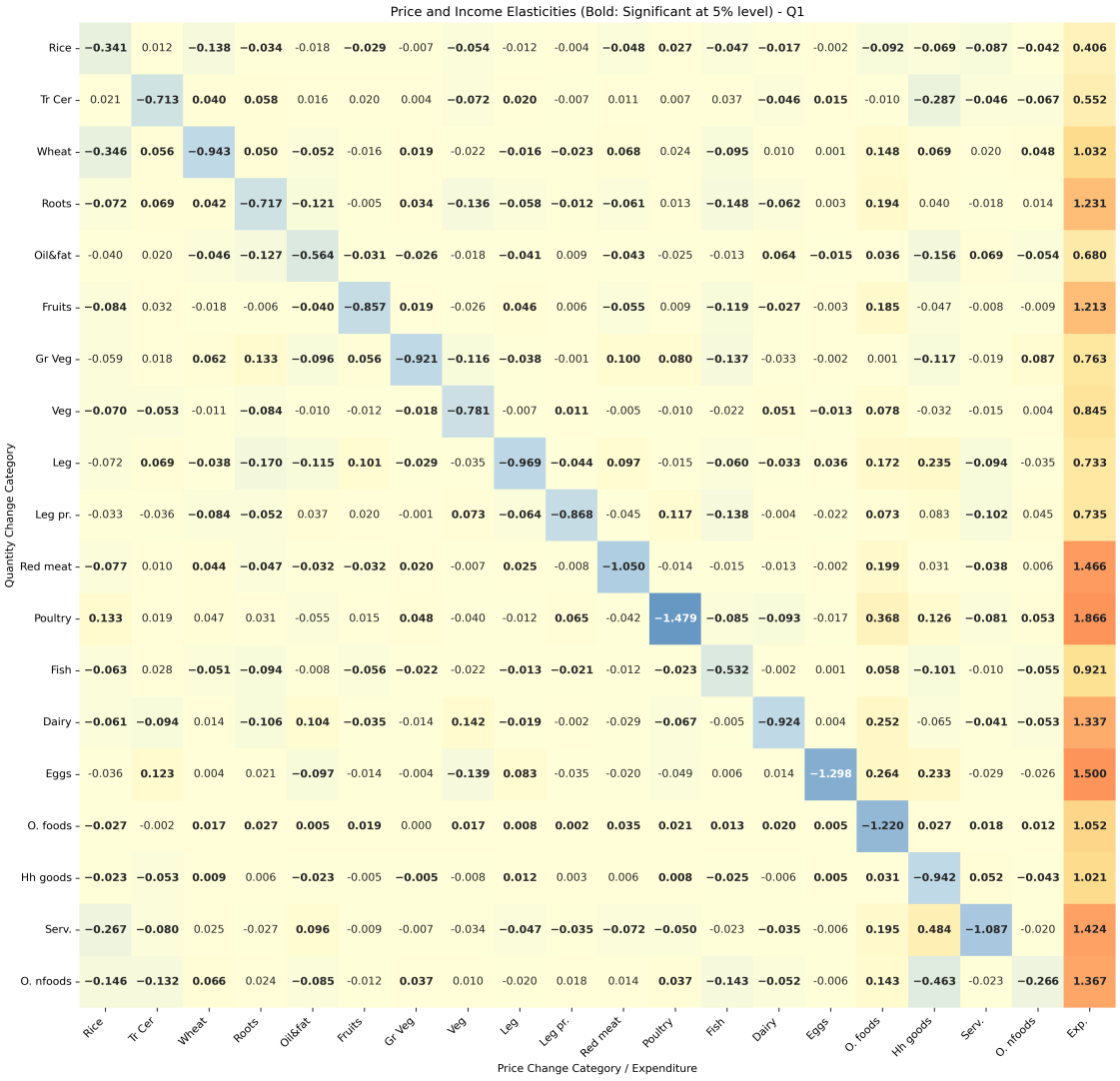
(b) Expenditure Quartile Q4

Income and price elasticities controlling for level 2 geographic unit fixed effects

Figure 8: Price and Income Elasticities

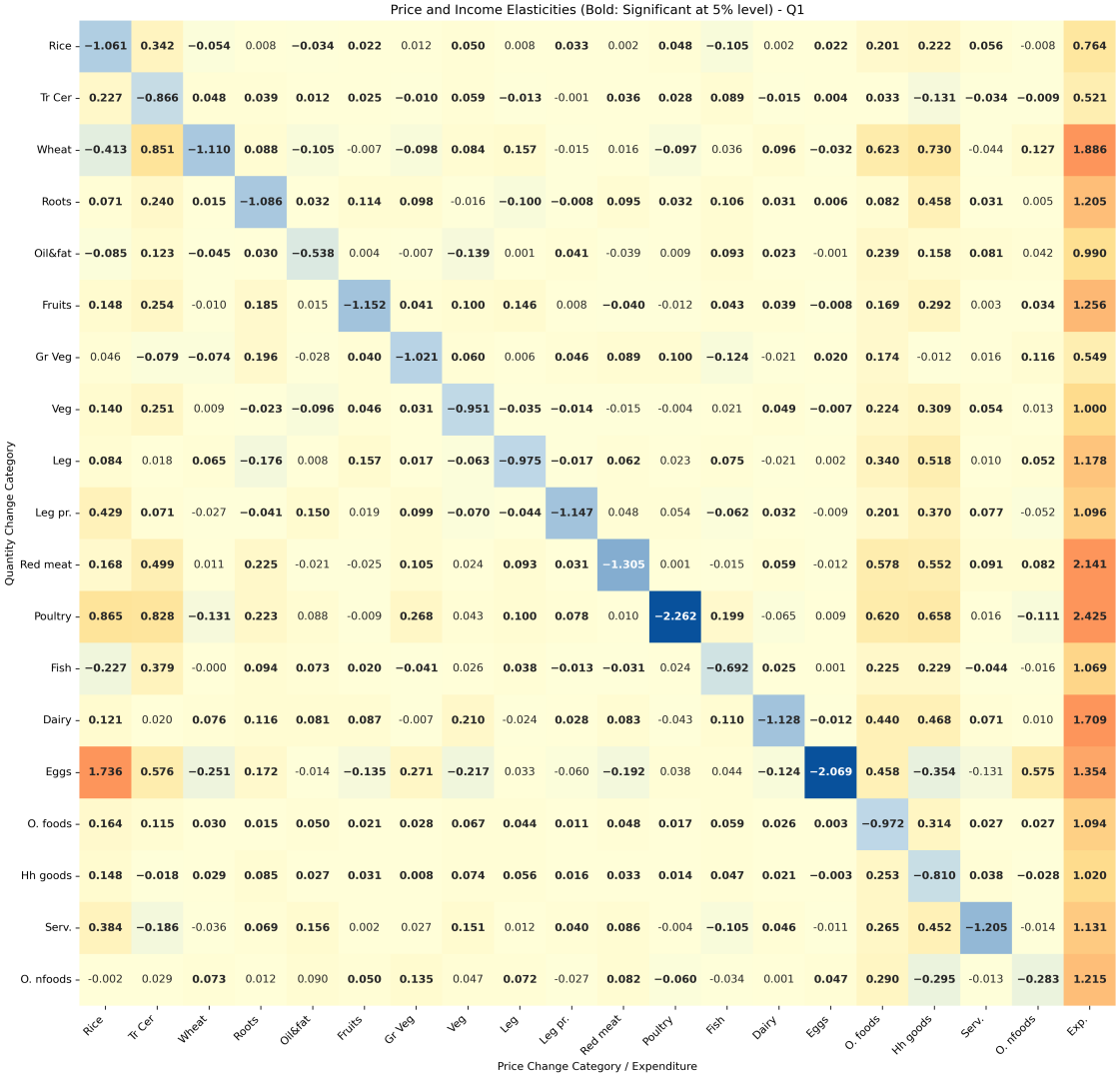


(a) Rural areas

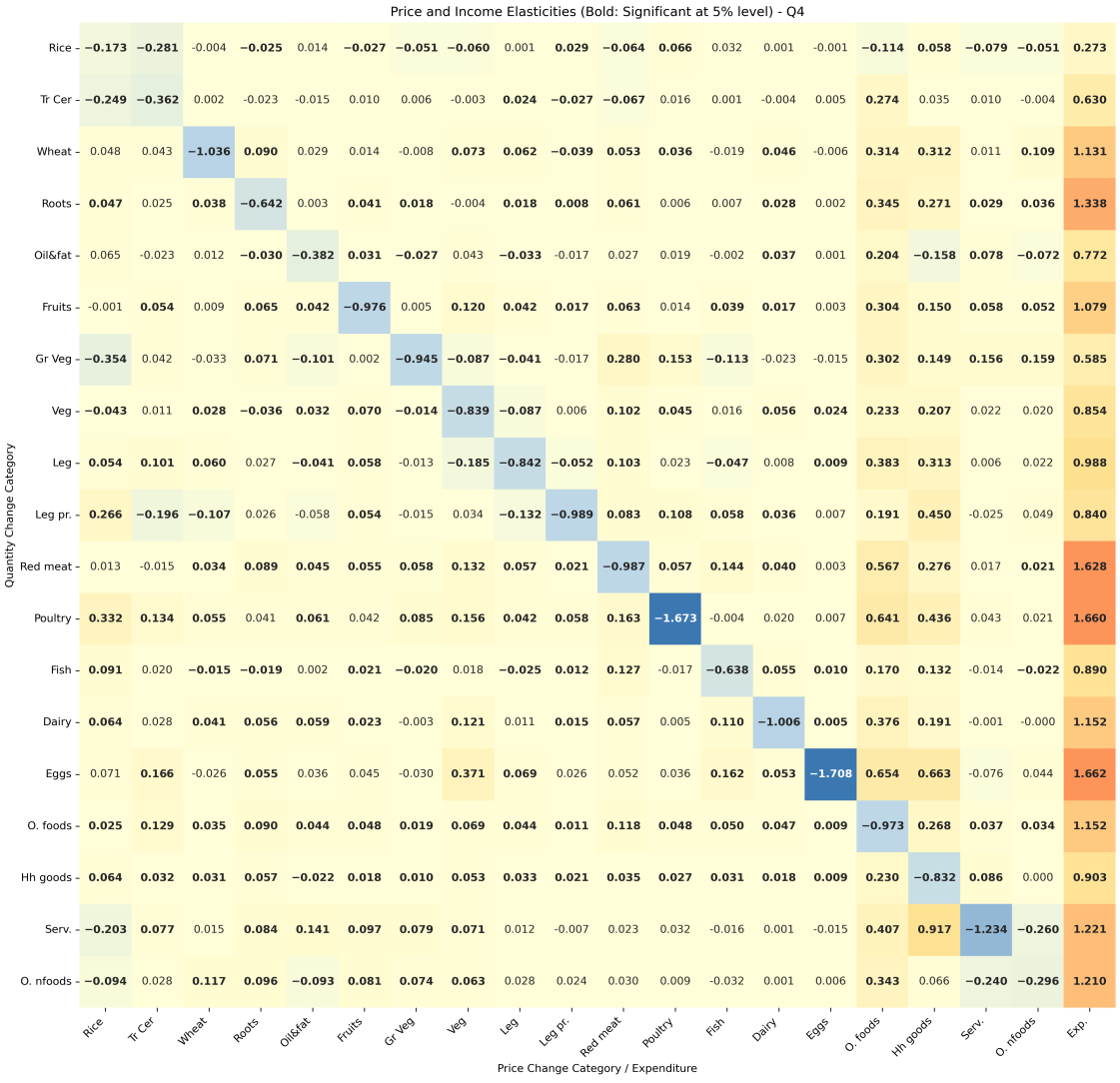


(b) Urban areas

Figure 9: Compensated Price and Income Elasticities, Rural

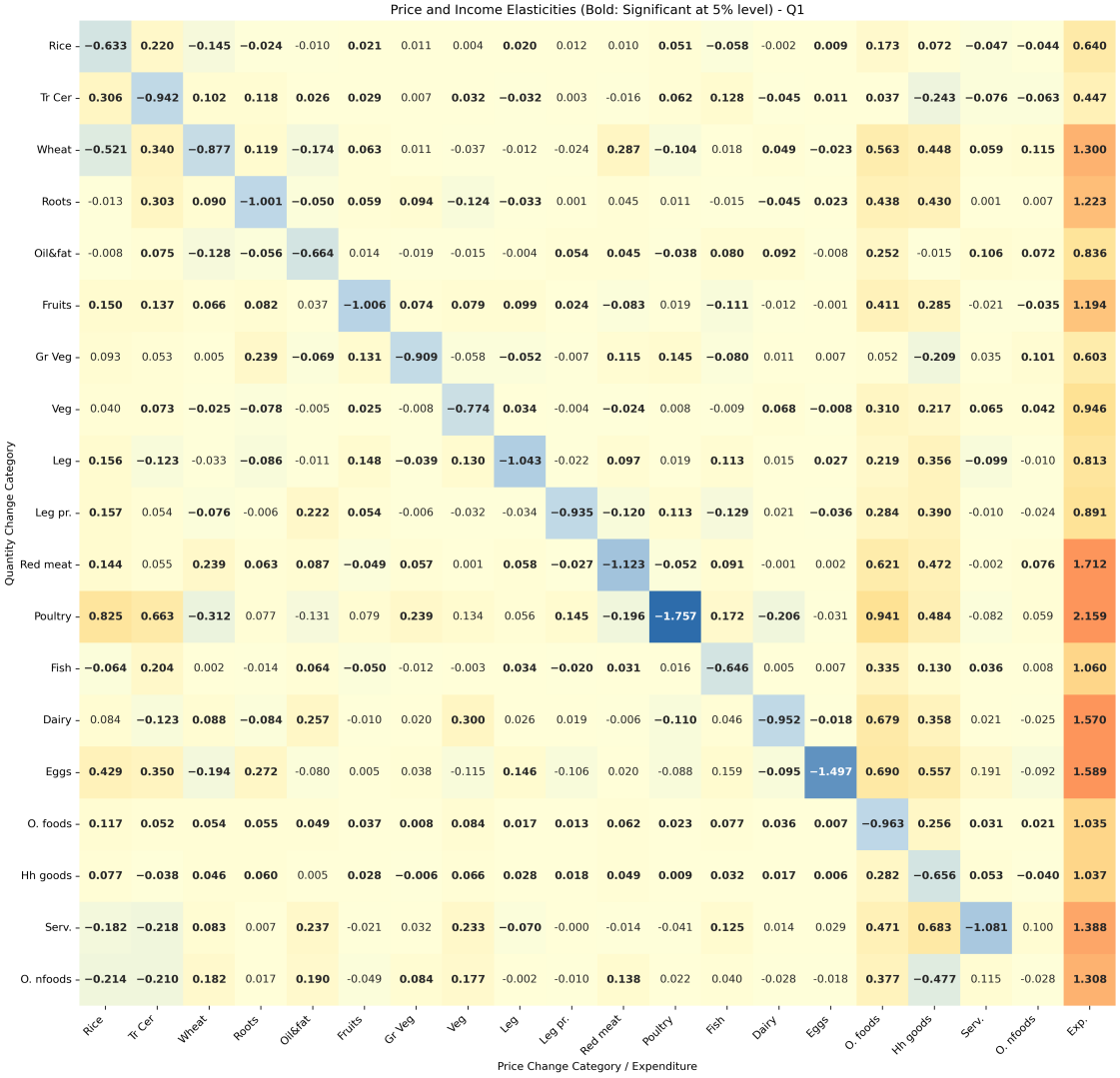


(a) Expenditure Quartile Q1

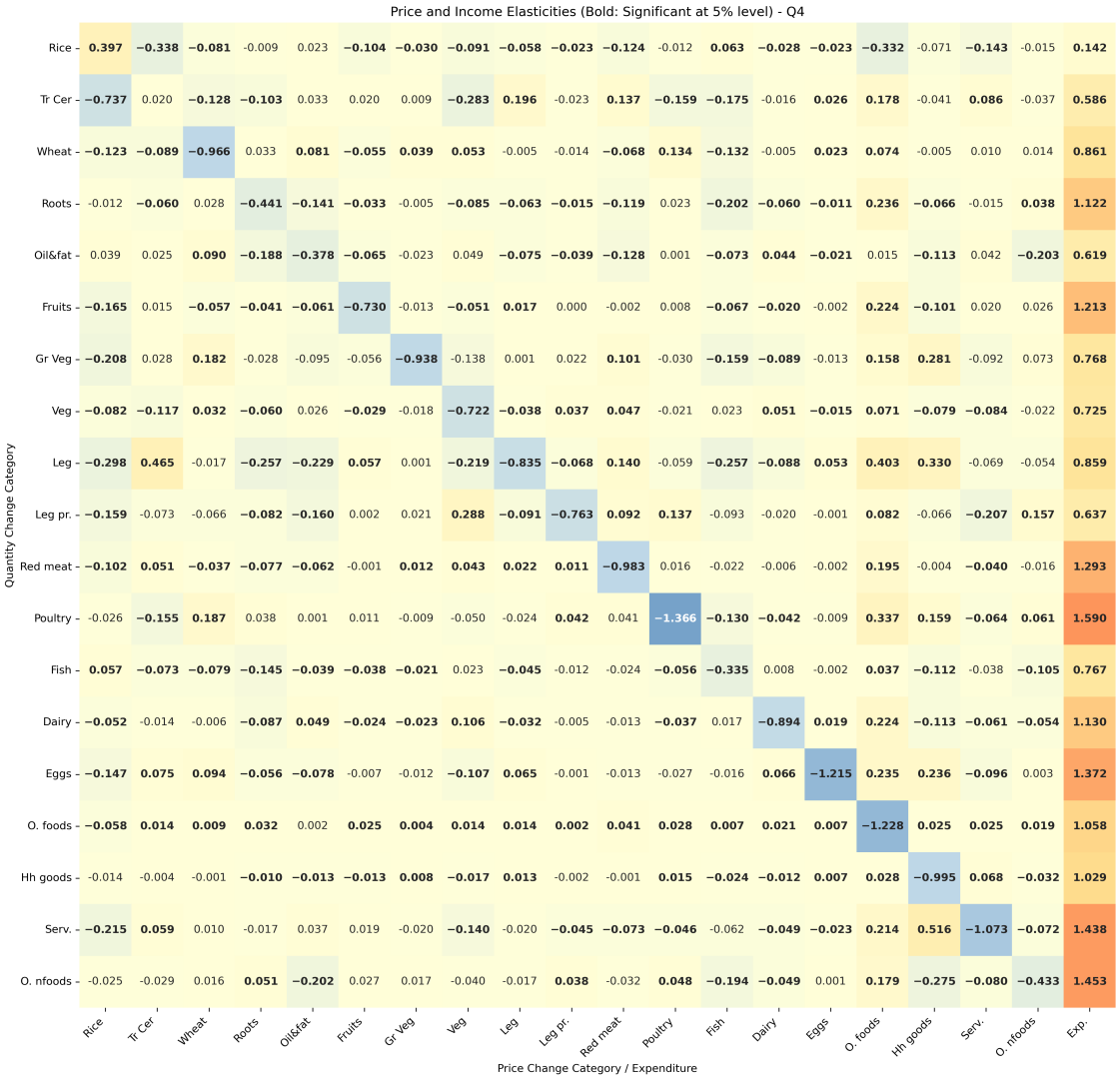


(b) Expenditure Quartile Q4

Figure 10: Compensated Price and Income Elasticities, Urban



(a) Expenditure Quartile Q1



(b) Expenditure Quartile Q4

Food group mapping

Table X: Food group mapping

Healthy Diet Basket food group	Demand system group
Starchy staples	Rice
	Traditional cereals
	Wheat
	Roots and tubers
Oils and fats	Oils and fats
Fruits	Fruits
Vegetables	Dark green leafy vegetables
	Other vegetables
Legumes, nuts, and seeds	Processed
	Unprocessed
Animal source foods	Red meat
	Poultry
	Fish
	Dairy
	Eggs
Excluded	Discretionary

Retail prices of biomass fuels

This section describes the detailed methodology for the collection of the monthly retail price data from the National Statistical Office of Malawi. The data are collected by the Price and Index Numbers section for monitoring inflation. The price data is collected in all major trading centers and cities across the country, namely 22 towns/trading centers selected to represent rural areas, and in 6 markets across the four cities to represent urban areas (two markets each are visited in Lilongwe and Blantyre, while only one market is visited in each Zomba and Mzuzu).

Price data collection covers fifteen population strata: three rural strata for three regions of the country (Northern, Central, and Southern regions) and twelve urban strata. The urban strata contain three income groups (high, medium, and low) for each of the four cities, Lilongwe, Blantyre, Zomba, and Mzuzu. The income groups are derived from the latest Integrated Household Survey data to account for differences in where households buy goods and services, which affect the prices and the type of products consumed.

Prices are collected every month, following a strict schedule that outlines the specific dates and location for data collection, the specific week of the month for the data entry process at each regional office, and the specific days for visiting each market. The schedule considers the market days of each market across the regions.

Data entry and preliminary analysis are done at regional offices, including validating the price data by comparing it with a paper questionnaire or contacting the sellers when large price changes are observed. The regional offices also calculate the geometric mean price of each item from the three samples before submitting data to headquarters. At the head office, the Statistician imputes missing prices using cell-mean imputation, which assumes that missing prices change in the same way as that of the item in the same elementary group for which prices are available.

Item selection

The pricing officers collect the prices of representative items, which are narrow specifications of goods and services, chosen to represent the broader item classes. All items covered in the current consumer price indices are broadly classified and presented using the Classification of Individual Consumption by Purpose (COICOP), which defines 12 major divisions (Table 2).

Items were selected based on household consumption patterns from the Fifth Integrated Household Survey (IHS-5), conducted from March 2019 to March 2020. The IHS-5 collected extensive information from a sample of households from every country district, covering the goods and services they bought or produced for own consumption.

Some population strata (rural, urban-high income, urban-medium income, and urban-low income) do not consume anything in some item classes, so their CPIs have fewer item classes. For instance, much as all strata consume rice, only high and middle-income groups consume Rice Super Fire, which is packed and sold in shops, unlike in rural areas or markets frequented

by low-income urban households, where rice is sold loose in open markets. Another example is Corn Flakes cereal, primarily consumed by urban households and excluded from the rural food list.

Purchasing the items

The NSO uses two approaches for collecting price data depending on the kind of outlet and the items involved. Most of the food items are sold in non-standardized units (i.e., heap of tomatoes, bunch of bananas). Price collectors are advised to purchase the highest-quality commodities for weighing. Likewise, depending on location, medium to large heaps of tomatoes are encouraged to be purchased for weighing to mimic normal consumers purchasing commodities in the market. All non-food items are sold in standardized units, except for charcoal and firewood.

Data collectors are given funds to purchase three samples of each commodity that is sold in non-standardized units. After purchasing three samples of each item, the samples are taken to the office or the nearest convenient location for weighing on a digital scale. The weight is recorded on the data collection form and later used together with the price to calculate the unit price in kilograms. Budget constraints may affect the ability of price collectors to purchase the items.

The pricing officers use two separate questionnaires to collect prices from all other points of sale (i.e., shops, restaurants, bars, schools, clinics, garages). The rural market questionnaire has 178 representative items, while the urban questionnaire has 310 items. One observation is taken from three different outlets for each item, resulting in a maximum of 18,300 individual price observations in shops. In practice, somewhat fewer price observations are collected, as there are not always three vendors for each items in all markets.

Average prices for the 2019-20 survey period

For the market fuels, firewood and charcoal, I use the price per kilogram of firewood or charcoal for the market and month in which the prices were collected. When market-month fuel prices are missing, I calculate average fuel prices for each district-month, district-quarter, region-urban/rural-month, and region-urban-rural/quarter. I use the lowest level of aggregation price available.

Nationally regulated fuels

Paraffin, LPG, and electricity are regulated by the MERA. MERA was established in 2004, following the 2003 National Energy Policy and the enactment of the Energy Regulation Act, No. 20. MERA's mandate is to regulate the energy sector in accordance with the legal and regulatory framework of the National Energy Policy, including the regulation of electricity and fuel tariffs.

ESCOM has various electricity tariff rates for electricity depending on the type of user. We use prepaid, single-phase tariffs for domestic uses (tariff code ET1). In 2018, these tariff

rates changed from being unit charges per kWh for all usage to a two-tiered rate, in which the rate per unit rises after an initial 50 kwH of usage.

MERA reviews electricity tariff increases if ESCOM submits a 'rate case' for approval or if the Automatic Tariff Adjustment Formula (ATAF) is triggered. The ATAF for electricity is triggered when the weighted sum of local inflation and the USD exchange rate deviates more than 5 percent. In 2014, MERA approved a 37 percent tariff increase request submitted by ESCOM, to be implemented incrementally over a four-year period (USAID 2018). In 2015, the Malawi Kwacha devalued by nearly a third compared to the US dollar and due to inflation, leading to a 30.67 percent tariff increase approved in January 2016 after the ATAF was triggered. MERA also regulates petroleum products, including LPG, according to an ATAF.

Between 2013 and 2018, the United States Government cooperated with the Government of Malawi through the Millennium Challenge Corporation Malawi Compact to improve the electricity situation in the country, resulting in major changes to the Malawian energy sector. The Compact involved restructuring of Malawi's energy market, including the unbundling of the vertically integrated Electricity Supply Corporation of Malawi (ESCOM). Prior to 2017, ESCOM fulfilled all electricity generation, transmission, and distribution functions for Malawi, without private-sector participation. In the Electricity Amendment Bill of 2016, amendments to the 2003 Electricity Act authorized separating ESCOM into two entities, leaving ESCOM as a transmission and distribution company and establishing the Electricity Generation Company Malawi Ltd (EGENCO) as the generation company. This was in part to enable private sector participation in the electricity generation market and improve the financial situation of the electricity sector (USAID). Various other development partners have also invested heavily in the Malawian energy sector, including the World Bank.

Estimates of cooking water

For legumes, I rely on recipes and descriptions from Mulei et al. (2013). For leafy vegetables, I assume a 3:1 vegetable-to-water ratio based on Malawian recipes (Pastakia; mal). For vegetables that are commonly added to other cooked meals or sauteed in oil, such as tomatoes and onions, I do not account for water for cooking.

Least-cost diet results by district

Table XI: Cost of a Healthy Diet with and without fuel costs, district averages

	Real MWK			2021 PPP		
	CoHD	CoHD + fuel costs	% diff.	CoHD	CoHD + fuel costs	% diff.
Balaka	704.05	989.99	40.30	2.91	4.08	40.30
Blantyre	652.00	912.49	40.37	2.61	3.65	40.37
Blantyre City	626.92	858.07	36.74	2.66	3.64	36.74
Chikwawa	604.21	886.09	48.40	2.45	3.59	48.40
Chiradzulu	572.81	988.78	72.80	2.32	4.00	72.80
Chitipa	489.60	632.23	29.26	2.05	2.64	29.26
Dedza	650.67	927.13	42.89	2.78	3.96	42.89
Dowa	617.15	805.87	30.95	2.62	3.42	30.95
Karonga	542.10	724.52	35.84	2.27	3.04	35.84
Kasungu	602.16	740.95	24.15	2.56	3.15	24.15
Likoma	1020.57	1284.58	26.44	4.34	5.45	26.44
Lilongwe	644.04	836.55	29.90	2.74	3.55	29.90
Lilongwe City	612.62	785.12	28.26	2.61	3.34	28.26
Machinga	713.15	1019.54	43.84	2.93	4.18	43.84
Mangochi	781.37	1086.23	38.02	3.25	4.51	38.02
Mchinji	691.73	914.32	31.62	2.93	3.87	31.62
Mulanje	550.11	890.18	60.10	2.26	3.65	60.10
Mwanza	588.26	900.13	52.97	2.43	3.72	52.97
Mzimba	606.63	785.05	29.52	2.53	3.27	29.52
Mzuzu City	585.37	733.58	25.42	2.50	3.14	25.42
Neno	637.14	1051.61	64.68	2.61	4.31	64.68
Nkhatabay	612.27	806.22	32.01	2.55	3.35	32.01
Nkhotakota	619.59	789.23	27.26	2.62	3.34	27.26
Nsanje	587.44	915.95	56.06	2.42	3.76	56.06
Ntcheu	592.78	820.60	39.96	2.52	3.48	39.96
Ntchisi	625.32	807.15	30.21	2.66	3.43	30.21
Phalombe	535.96	931.97	73.45	2.19	3.81	73.45
Rumphi	568.28	759.44	34.57	2.36	3.15	34.57
Salima	611.65	783.46	28.71	2.59	3.31	28.71
Thyolo	568.67	979.87	71.14	2.33	4.02	71.14
Zomba	634.35	926.17	47.59	2.55	3.72	47.59
Zomba City	564.62	837.96	48.65	2.40	3.57	48.65
Total	614.71	865.48	41.43	2.56	3.60	41.43

Note: Estimates are market visit averages, with no household weights applied. Spatial and temporal deflator was derived from the IHS5 survey.

Estimates of the cost of cooking in the literature

Most studies that do address cooking fuel costs directly focus on a small subset of foods or commonly consumed meals. Carlsson-Kanyama estimate the electricity needed to cook portions of wheat, spaghetti, pasta, barley, rice, potatoes, couscous and mashed potatoes in selected cooking appliances in Sweden. The authors find large efficiences for cooking multiple portions, and in using electric kettles for boiling water, and estimate 3.1-4.9 MJ of energy are needed per kilogram of spaghetti, as compared to 0.7-3.5 MJ/kg of rice using entirely electricity-based cooking methods.

Cooking costs associated with select food items to design or assess the performance of improved cookstoves have made key contributions to this literature. A **cct!** (**cct!**) carried out in Kampala compared the time, energy, and cost of cooking various popular local dishes in different cookstoves, finding electric pressure cookers to be the most effective on all three metrics for cooking meals that cook for a long time, such as beans, and comparable on these metrics for sauteeing vegetables, etc. LPG was found to be the least cost-effective, while charcoal was the least-expensive yet most time-consuming MECS.

Kajumba et al. (2022) also examine cooking costs in Uganda, developing a method to estimate the theoretical energy needs to cook specific, and comparing theoretical needs with actual measurements. They find measured energy levels significantly higher than theorized energy needs, and ultimately calculate that approximately 2.6 kg of firewood are needed to cook a kilogram of dry beans, compared to 1 kg of firewood per kg of maize flour.

In the meal-based tradition, Nerini et al. (2017) estimate a model called the "levelized cost of cooking a meal" based on the observation of 15 households in a county in Kenya for one month. The authors estimate that cooking a standard meal, defined as a meal for a family of four cooked for 45 minutes on an improved charcoal cookstove, requires an average of 3.6 megajoules (MJ) of final energy, or 12.15 MJ of primary energy. The authors also find that improved firewood and charcoal cookstoves can reduce total costs compared to traditional firewood, while cooking with LPG and electricity result in higher costs. Similar work by Singh et al. (2021) estimates cooking energy per household meal using aggregate energy use in India, and find that approximately 4.2 MJ are needed per household per meal, of which 1.5 MJ are lost to water vaporization during cooking, 0.8 MJ are used to heat food to boiling temperature, and 1.9 MJ are lost to convection from cookware. Neither method explicitly considers the contents of the meal being prepared.

Table XII: Characteristics of selected foods, reported consumption

	Quantity consumed (kg EP/AE/day)	Specific heat capacity	TE, food	TE, water	TE, simmer	TE, total	Firewood (kg)	Cost of firewood (2021 PPP)
101	0.73	1.86	126.76	646.70	321.73	1095.18	0.46	0.14
	(0.86)	(0.00)	(3.45)	(12.98)	(325.32)	(326.87)	(0.14)	(0.08)
106	0.08	1.90	130.16	648.17	1800.09	2578.53	1.07	0.34
	(0.16)	(0.00)	(3.58)	(13.33)	(2099.35)	(2100.20)	(0.88)	(0.35)
201	0.07	3.09	212.08	324.24	2713.76	3252.88	1.36	0.43
	(0.18)	(0.00)	(5.54)	(6.27)	(3619.13)	(3621.10)	(1.51)	(0.56)
301	0.01	1.94	133.41	974.37	15629.50	16761.58	6.98	2.42
	(0.05)	(0.00)	(3.76)	(20.48)	(19378.18)	(19388.92)	(8.08)	(3.73)
803	0.05	1.98	135.62	0.00	588.00	723.90	0.30	0.10
	(0.05)	(0.00)	(3.76)	(0.00)	(866.58)	(866.92)	(0.36)	(0.13)

Note: TE = theoretical energy (KJ/kg), EP = edible portion. All values are per kilogram of food. Quantities are energy-adjusted, per adult equivalent per day. Household sampling weights were applied.

Table XIII: Cooking fuel costs per household, by main fuel cost

	Firewood	Charcoal	Electricity	LPG	All fire	Charcoal	Elec	All fuel
Urban North	0.83	0.34	0.16	0.74	0.45	0.71	0.30	1.46
	(0.62)	(0.15)	(0.09)	(0.66)	(0.78)	(0.86)	(0.66)	(1.29)
Urban Central	0.59	0.33	0.17	0.38	0.24	0.86	0.38	1.48
	(0.24)	(0.18)	(0.08)	(.)	(0.57)	(0.85)	(1.83)	(2.08)
Urban South	0.49	0.58	0.17	0.62	0.37	0.75	0.41	1.54
	(0.24)	(0.22)	(0.05)	(.)	(0.72)	(0.89)	(0.76)	(1.43)
Rural North	0.83	0.43	0.16		1.12	0.11	0.03	1.27
	(0.61)	(0.25)	(0.08)		(1.15)	(0.38)	(0.19)	(1.20)
Rural Central	0.67	0.29	0.20		0.96	0.10	0.01	1.07
	(0.39)	(0.15)	(0.05)		(0.91)	(0.37)	(0.12)	(0.98)
Rural South	0.43	0.41	0.16		1.12	0.10	0.03	1.25
	(0.23)	(0.21)	(0.05)		(0.96)	(0.37)	(0.22)	(1.02)
Total	0.58	0.41	0.17	0.56	0.93	0.21	0.08	1.23
	(0.40)	(0.22)	(0.07)	(0.39)	(0.96)	(0.55)	(0.57)	(1.18)
Observations	8825	2278	162	5	11390	11390	11254	11254

Note: Cost in 2021 PPP/HH/day if all cooking was done with main fuel type.

Comparison of results with previous estimates

The estimates reported in table XXI are lower but conceptually consistent with those reported by Singh et al. (2021), who estimate cooking energy per household meal in India, and find that approximately 4.2 MJ are needed per household per meal, of which nearly half (1.9 of 4.2 MJ) are lost to convection from cookware. According to data collected in 2019 by Gallup and Cookpad 2022 on meals cooked per week by Malawian households, I estimate that households cook close to one meal per day.[1] Given that I do not account for convection losses from cookware in our approach and households average about a meal per day in Malawi, our findings of the lower bound energy needs per household per day in Malawi align with those reported elsewhere.

[1] I use aggregate estimates of the number of lunches and dinners cooked at home per week from 2019 among households categorized by size. No comparable data was collected in 2020.

Reported total fuel expenditures at the household level can be compared with our estimated cooking costs. Reported expenditures are much higher than estimated costs (table **??**). I propose several explanations for these discrepancies. Theoretical energy needs are expected to provide a lower bound for energy needs. Comparisons of theoretical and measured energy by Kajumba et al. (2022) show differences of approximately 200 % for fresh and dry beans, likely due to thermal losses that are not captured in our analysis.

Another possibility is that households collect or purchase large quantities of energy upfront, for example, 50-kilogram bags of charcoal or electricity credits. When these expenditures are translated into cost per day from the various reporting periods in the survey, costs per day may not accurately reflect the consumption period. For example, a household could purchase a large number of electricity units in the reporting month, but use the electricity over the course of two months; this would not be reflected in our calculation of expenditures per day.

Detailed methods

Reported household food consumption

1. Calculate the quantity consumed of each food consumed per household. The total quantity the household reported consuming is energy-adjusted and reported in kilograms per week, the reporting period of the consumption module.
2. Estimate the specific heat capacity of each food, or the amount of heat that must be added to the mass of the food to increase one degree Celsius. Food composition data is required for this step.
3. Estimate the quantity of water needed to cook each food.
4. Calculate the theoretical energy required to heat both the food and water from the ambient temperature to the boiling (water) or cooking temperature (assumed to be 90°C for food).
5. Calculate how many kilograms or units of fuel would be need to supply the theoretical energy needs, given the calorific value of each food in Malawi and the efficiency of stoves used.
6. Calculate the cost of the total fuel requirement at prevailing local prices.

Table XIV: Characteristics of all cooked foods, food group 1

	Specific heat capacity	TE, food	TE, water	TE, simmer	TE, total
Maize ufa mgaiwa (normal flour)	1.86	0.03	0.17	0.09	0.30
Maize ufa refined (fine flour)	1.77	0.03	0.17	0.10	0.31
Maize ufa madeya (bran flour)	1.86	0.03	0.17	0.22	0.43
Maize grain (not as ufa)	1.72	0.04	0.19	1.40	1.63
Green maize	3.30	0.17	0.00	0.48	0.65
Rice	1.90	0.04	0.19	0.53	0.75
Finger millet (mawere)	1.70	0.03	0.26	1.62	1.91
Sorghum (mapira)	1.78	0.03	0.27	0.66	0.96
Pearl millet (mchewere)	1.83	0.03	0.25	0.37	0.66
Wheat flour	1.96	0.00	0.00	0.00	0.00
Bread	2.47	0.07	0.00		
Buns, scones	2.80	0.09	0.00		
Spaghetti, macaroni, pasta	1.87	0.03	0.33	0.79	1.16
Breakfast cereal	1.66	0.03	0.00		
Infant feeding cereals	1.84	0.04	0.28	0.32	0.64
Cassava tubers	3.09	0.13	0.20	1.75	2.08
Cassava flour	1.87	0.04	0.28	0.20	0.52
White sweet potato	3.55	0.27	0.36	1.32	1.95
Orange sweet potato	3.48	0.29	0.40	1.71	2.40
Irish potato	3.70	0.37	0.47	3.19	4.02
Potato crisps	1.76	0.00	0.00	0.00	0.00
Plantain, cooking banana	3.27	0.18	0.26	2.00	2.45
Cocoyam (masimbi)	3.20	0.16	0.24	2.31	2.72
Maize, boiled/roasted (vendor)	3.49	0.00	0.00	0.00	0.00
Cassava, boiled (vendor)	3.18	0.00	0.00	0.00	0.00
Boiled sweet potatoes	3.52	0.00	0.00	0.00	0.00
Roasted sweet potatoes	3.52	0.00	0.00	0.00	0.00
Banana-maize cake(zikondamoyo)	2.82	0.00	0.00	0.00	0.00
Cassava, roasted (vendor)	3.18	0.00	0.00	0.00	0.00
Sorghum flour (ufa wa mapira)	1.83	0.03	0.26	0.09	0.38
Total	2.49	0.11	0.19	0.82	1.14
Observations	40792	40356	40356	36531	36506

Note: TE = theoretical energy in KJ/kcal.

Specific heat capacity and theoretical cooking costs per food item

Table XV: Characteristics of all cooked foods, food group 2

	Specific heat capacity	TE, food	TE, water	TE, simmer	TE, total
Margarine - Blue band	2.30	0.02	0.00	0.14	0.16
Butter	2.37	0.00	0.00	0.00	0.00
Cooking oil	1.98	0.02	0.00	0.06	0.08
Total	2.01	0.02	0.00	0.07	0.08
Observations	10463	10418	10418	10425	10418

Note: TE = theoretical energy in KJ/kcal.

Table XVI: Characteristics of all cooked foods, food group 3

	Specific heat capacity	TE, food	TE, water	TE, simmer	TE, total
Onion	3.89	0.67	0.00	8.78	9.45
Cabbage	3.95	0.85	0.00	2.33	3.18
Rape (tanoposi)	3.86	0.72	0.29	4.19	5.19
Pumpkin leaves (nkhwani)	3.85	0.82	0.51	23.96	25.28
Chinese cabbage (pe-tsai)	4.03	1.73	0.68	13.20	15.59
Other cultivated green leafy veg.	3.94	0.99	0.40	6.72	8.12
Gathered wild green leaves	3.74	0.64	0.27	5.48	6.38
Tomato	4.03	1.53	0.00	4.69	6.22
Cucumber	4.05	1.83	0.00	0.00	1.83
Pumpkin	3.96	1.04	0.12	2.94	4.11
Okra/Therere	3.69	0.41	0.35	8.71	9.46
Tinned vegetables	3.92				
Mushroom	3.95	0.85	0.00	4.96	5.81
Sawawa	3.64	0.32	0.00	0.63	0.95
Carrots	3.84				
Mustard greeens / mpiru	3.94				
Eggplant	3.85				
Total	3.90	0.96	0.22	8.92	10.10
Observations	48236	47746	47746	47779	47746

Note: TE = theoretical energy in KJ/kcal.

Table XVII: Characteristics of all cooked foods, food group 4

	Specific heat capacity	TE, food	TE, water	TE, simmer	TE, total
Mango	3.75	0.00	0.00	0.00	0.00
Banana	3.52	0.00	0.00	0.00	0.00
Citrus	3.83	0.00	0.00	0.00	0.00
Pineapple	3.81	0.00	0.00	0.00	0.00
Papaya	3.86	0.00	0.00	0.00	0.00
Guava	3.68	0.00	0.00	0.00	0.00
Avocado	3.54	0.00	0.00	0.00	0.00
Wild fruit	3.83	0.00	0.00	0.00	0.00
Apple	3.80	0.00	0.00	0.00	0.00
Peach	0.00	0.00	0.00	0.00	0.00
Custard apple / mipoza / Mexican apple	3.43				
Watermelon	3.98				
Total	3.67	0.00	0.00	0.00	0.00
Observations	11258	10895	10895	10895	10895

Note: TE = theoretical energy in KJ/kcal.

Table XVIII: Characteristics of all cooked foods, food group 5

	Specific heat capacity	TE, food	TE, water	TE, simmer	TE, total
Bean, white	1.94	0.04	0.29	4.72	5.05
Bean, brown	1.53	0.03	0.28	6.90	7.22
Pigeonpea (nandolo)	1.92	0.04	0.28	3.18	3.49
Groundnut flour	1.91	0.02	0.27	0.79	1.08
Soyabean flour	1.91	0.03	0.33	0.27	0.63
Ground bean (nzama)	1.44	0.03	0.30	7.49	7.83
Cowpea (khobwe)	1.69	0.03	0.34	4.71	5.08
Macademia nuts	1.95	0.02	0.00	3.38	3.40
Groundnut (shelled)	1.90	0.02	0.00		
Groundnut (unshelled)	1.90	0.02	0.00		
Groundnut fresh (unshelled)	2.04	0.02	0.06	1.87	1.96
Boiled groundnuts	2.92	0.00	0.00	0.00	0.00
Roasted groundnuts	1.91	0.00	0.00	0.00	0.00
Other (specify)	1.65	0.00	0.00	0.00	0.00
Soya pieces (e.g., TopSoy)	0.00	0.00	0.11	0.29	0.40
Soya (beans)	1.63	0.00	0.00	0.00	0.00
Velvet bean/mucuna	1.65	0.00	0.00	0.00	0.00
Total	1.78	0.03	0.23	3.38	3.67
Observations	21671	21032	21032	18323	18313

Note: TE = theoretical energy in KJ/kcal.

Theoretical energy needs, regression analysis

Table XIX: Characteristics of all cooked foods, food group 6

	Specific heat capacity	TE, food	TE, water	TE, simmer	TE, total
Eggs	3.62	0.17	0.00	2.86	3.02
Beef	3.47	0.25	0.32	16.82	17.39
Goat	3.41	0.14	0.19	3.89	4.22
Pork	3.29	0.09	0.00	3.38	3.46
Mutton	3.29	0.09	0.12	2.62	2.83
Chicken	3.59	0.19	0.19	3.11	3.49
Other poultry	3.55	0.00	0.00	0.00	0.00
Small animal	3.52	0.17	0.00	5.12	5.29
Termites, other insects	1.94	0.00	0.00	0.00	0.00
Tinned meat or fish	3.28	0.09	0.00	0.85	0.94
Fish Soup/Sauce	3.95				
Chicken/Pieces	3.59	0.19	0.19	19.25	19.64
Fresh milk	3.89	0.00	0.00	0.00	0.00
Powdered milk	1.84	0.00	0.00	0.00	0.00
Chambiko - soured milk	3.90	0.00	0.00	0.00	0.00
Yoghurt	3.84	0.00	0.00	0.00	0.00
Cheese	2.75	0.00	0.00	0.00	0.00
Eggs, boiled (vendor)	3.55	0.00	0.00	0.00	0.00
Chicken (vendor)	3.31	0.00	0.00	0.00	0.00
Meat (vendor)	3.33	0.00	0.00	0.00	0.00
Fish (vendor)	3.34	0.00	0.00	0.00	0.00
Sun-dried fish (large)	1.98	0.04	0.00	0.71	0.75
Sun-dried fish (medium)	2.56	0.05	0.00	6.88	6.93
Sun-dried fish (small)	2.20	0.04	0.00	3.97	4.01
Fresh fish (large)	3.50	0.25	0.00	4.51	4.76
Fresh fish (medium)	3.51	0.21	0.00	4.40	4.61
Fresh fish (small))	3.55	0.17	0.00	4.02	4.19
Smoked fish (large)	2.08	0.04	0.00	4.85	4.89
Smoked fish (medium)	3.06	0.11	0.00	10.73	10.83
Smoked fish (small)	2.97	0.10	0.00	11.84	11.94
Total	3.13	0.11	0.04	4.87	5.02
Observations	27587	27188	27188	27206	27188

Note: TE = theoretical energy in KJ/kcal.

Table XX: Characteristics of all cooked foods, food group 7

	Specific heat capacity	TE, food	TE, water	TE, simmer	TE, total
Biscuits	0.00	0.00	0.00	0.00	0.00
Infant feeding formula	3.77	0.00	0.00	0.00	0.00
Sugar	1.55	0.00	0.00	0.00	0.00
Sugar cane	3.91				
Salt	1.10				
Spices	1.87	0.00	0.00	0.00	0.00
Yeast, baking powder, etc.	0.41				
Tomato sauce (bottle)	3.34	0.00	0.00	0.00	0.00
Hot sauce (Nali, etc.)	3.31	0.00	0.00	0.00	0.00
Jam, jelly	2.35	0.00	0.00	0.00	0.00
Sweets, candy, chocolates	1.58	0.00	0.00	0.00	0.00
Honey	2.00	0.00	0.00	0.00	0.00
Chips (vendor)	2.78	0.00	0.00	0.00	0.00
Mandazi, doughnut (vendor)	2.84	0.00	0.00	0.00	0.00
Samosa (vendor)	3.30	0.00	0.00	0.00	0.00
Popcorn	1.79	0.00	0.00	0.00	0.00
Coffee	4.16	0.00	0.00	0.00	0.00
Cocoa, Milo	1.62	0.03	0.09		
Squash (Sobo concentrate)	3.86	0.00	0.00	0.00	0.00
Fruit juice	3.84	0.00	0.00	0.00	0.00
Freezes (flavoured ice)	3.66	0.00	0.00	0.00	0.00
Soft drinks	3.91	0.00	0.00	0.00	0.00
Chibuku (commercial traditional-style beer)	3.96	0.00	0.00	0.00	0.00
Bottled water	4.18				
Maheu	0.00				
Bottled / canned beer (Carlsberg, etc.)	3.91	0.00	0.00	0.00	0.00
Thobwa (fermented cereal-based drink)	0.00				
Traditional beer (masese)	3.96	0.00	0.00	0.00	0.00
Wine or commercial liquor	3.66	0.00	0.00	0.00	0.00
Locally brewed liquor (kachasu)	2.78	0.00	0.00	0.00	0.00
Other (specify)	0.00				
Kamba	0.00				
Total	1.81	0.00	0.00	0.00	0.00
Observations	41283	18607	18607	18579	18579

Note: TE = theoretical energy in KJ/kcal.

Table XXI: Theoretical energy per household

	(1) Food	(2) Water	(3) Simmer	(4) Total
Central	0.045***	0.004	0.071	0.114
	(0.009)	(0.017)	(0.083)	(0.086)
South	0.008	0.017	-0.000	0.020
	(0.008)	(0.017)	(0.088)	(0.090)
Rural	0.015*	0.123***	-0.433***	-0.308***
	(0.009)	(0.019)	(0.079)	(0.084)
Central × Rural	-0.013	0.004	-0.685***	-0.674***
	(0.013)	(0.023)	(0.098)	(0.105)
South × Rural	-0.019	-0.002	-0.465***	-0.454***
	(0.012)	(0.023)	(0.101)	(0.107)
Adult equivalents	0.125***	0.336***	0.071***	0.530***
	(0.002)	(0.003)	(0.008)	(0.009)
Constant	0.007	-0.119***	3.154***	3.020***
	(0.009)	(0.016)	(0.071)	(0.074)
Mean	0.50	1.26	2.67	4.41
N	11390	11390	11390	11390
F-Stat	746.28	2479.45	139.95	667.98

Note: Robust standard errors with household weights.