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The Future of Food Demand

A Global Meta-Analysis and Projections of Income and Price Elasticities

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ABSTRACT

Understanding how food demand responds to household income and price changes is essential for anticipating global food needs and designing effective food policies. Yet existing elasticity estimates vary widely due to differences in data, estimation methods, and study settings. This study aims to assess how empirical choices influence elasticity values and examine theory-based predictions related to income growth and inequality, urbanization, and demographic change. It provides the most comprehensive global systematic literature review and meta-analysis of income and price elasticities to date, compiling over 13,000 elasticity estimates from 215 peer-reviewed studies published between 1974 and 2022. We estimate two-level random effects meta-regressions and use the results to generate predicted elasticities for nine food groups by world region. While most data and methodological choices have little effect on price elasticity estimates, income elasticities are influenced by factors such as demand model type, use of conditional specifications, and the choice of expenditure measure. We find empirical support for Engel's Law but only partial support for Bennett's Law. Income elasticities are positively associated with urbanization, particularly in lower-income countries, and negatively associated with population aging. By projecting income elasticities through 2050 under alternative Shared Socioeconomic Pathways, we show that ignoring structural shifts in sociodemographics can yield meaningfully different estimates of future food demand.

Keywords: Food demand, income elasticity, price elasticity, systematic review, meta-analysis, projection

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1 Introduction

The theoretical foundations of consumer demand trace back to David Ricardo's early 19th-century work on taxation and income distribution (Ricardo, 1821), which highlighted how purchasing power influences consumption behavior. This was a precursor to modern concepts of income elasticity of demand, i.e., the proportional response of quantity demanded to a change in real income. Later, Marshall (1890)'s *Principles of Economics* formalized the relationship between prices, marginal utility, and the quantity of goods demanded. Central to this framework was the notion of price elasticity of demand, i.e., the proportional response of quantity demanded to a change in price, which remains a cornerstone of both neoclassical demand theory and empirical welfare analysis.

Estimated elasticities of demand play a critical role in applied economics. First, they reflect revealed consumer preferences and provide critical information about how people's consumption is expected to change when household income or the prices of food and non-food goods and services change, as a result of economic growth or policy interventions. Economic theory has long offered structured predictions on the food consumption effects of income growth and demographic shifts. The first formulated relationship between food consumption and household income is Engel's Law, which posits that, as income increases, the proportion spent on food decreases (Engel, 1857). Formulated much later, Bennett's Law describes a typical pattern of food consumption changes in the context of agricultural and economic development. It postulates that, with rising income, household consumption shifts away from calorie-dense starchy staple foods toward more diverse and nutrient-rich foods (Bennett, 1941). Second, estimated elasticities of demand are essential inputs in a wide range of economic models for a variety of analytical purposes, including models for business strategy development, market and trade analysis, and partial general equilibrium models, to assess the impacts of economic shocks and policies on development outcomes. One of the most immediate purposes of such models, especially in a developing context, is projecting future food demand in populations. While it is widely accepted that demand will continue to rise over the coming decades, especially in low- and middle-income countries (LMIC), the rate at which this growth will occur, and the associated patterns of typical consumption shifts between distinct food groups, are open questions.

Despite a large empirical literature estimating income and price elasticities of food demand across countries, time periods, and food groups, reported values vary widely. This heterogeneity reflects differences in data sources, demand models, estimation strategies, and contextual settings. However, the extent to which data and methodological choices systematically shape elasticity estimates remains poorly understood. This paper asks: 1) Do empirical choices, including data characteristics and estimation methods, explain the observed variation in food demand elasticities? 2) Are theoretical predictions regarding the role of sociodemographic factors empirically supported? 3) How is food demand expected to vary with projected sociodemographic changes?

To answer these questions, we first conduct a global systematic literature review of empirical food demand estimation studies. We compile over 13,000 income and price elasticity estimates extracted from 216 peer-reviewed studies covering five continents, along with detailed information on their data characteristics and estimation methods. The meta-sample data is merged with country-level sociodemographic indicators. Second, we perform a meta-regression analysis using a two-level random intercept model to quantify how methodological choices, data characteristics, and sociodemographic factors contribute to the variation in reported elasticities. Population-weighted average predicted income and price elasticities are estimated for nine food groups by world region as of 2021. Third, we use these estimated relationships to project global food demand through 2050, allowing elasticities to evolve in line with scenario-based projections of sociodemographic characteristics.

Our meta-analysis synthesizes demand elasticities from the literature and offers a framework for interpreting the wide variation in published estimates. It quantitatively assesses how specific empirical choices and evolving sociodemographic contexts shape these demand parameters that are crucial for policy analysis and market modeling. The strength of this approach is its ability to generate robust, generalizable meta-estimates. The trade-off is a loss of context-specific detail. Our predicted elasticities should therefore be seen as a standardized reference value, to be refined with local data when possible. Lastly, the projection exercise demonstrates how structural sociodemographic shifts can alter consumption trajectories and illustrate the limitations of assuming static demand elasticities in long-term modeling.

The meta-regression results indicate that some estimation methods help explain empirical differences in elasticity estimates. Income elasticities estimated using conditional demand[1] tend to yield higher values,

[1] Conditional elasticities measure the demand response for a specific food product or group under the assumption that certain factors, such as total expenditure on food or the consumption of related products, remain fixed. These elasticities capture substitution effects within a specific category of food but do not account for shifts in consumption across broader food or non-food categories. In contrast, unconditional elasticities measure demand responses without such restrictions, reflecting adjustments across all food and non-food items. In our meta-sample and meta-regression analysis, both conditional and unconditional elasticities are included. However, we incorporate a dummy variable to distinguish between them, as they represent different scopes of demand response and should not be treated as equivalent measures.

while those estimated using household income rather than total expenditure to measure income elasticities, or using a quadratic almost ideal demand system (QUAIDS), tend to yield lower values. As expected, Hicksian (compensated) price elasticities are larger in magnitude than Marshallian (uncompensated) ones.[2]

In line with Engel's Law, we find that income elasticities decline as gross domestic product (GDP) per capita rises. This effect is more pronounced in higher urbanized settings. However, evidence for Bennett's is limited. While income elasticities for food away from home (FAFH) rise with real income —consistent with their discretionary nature —the decline in income elasticities for grains & starchy staples is not significantly steeper than that for total food, and income elasticities for animal-sourced foods (ASF) do not rise significantly with real income. Income inequality shows little explanatory power in shaping elasticity estimates. Urbanization is associated with higher income elasticities across most food groups, particularly in LMIC contexts, likely reflecting increased market access and dietary diversification. This pattern reverses for FAFH, suggesting early adoption and saturation effects in urban settings. Population aging is linked to lower income elasticities, consistent with reduced caloric needs and more stable dietary habits among older individuals.

Our population-weighted average predicted income and price elasticities are broadly consistent with established findings in the literature, highlighting significant regional and food-group variation. Estimated income elasticities are the highest in Africa and for more discretionary food groups, such as ASF (0.98) and FAFH (1.29). They are the lowest for grains & starchy staples (0.59), which form the bulk of diets in many LMIC. Demand for necessities with fewer close substitutes, such as grains & starchy staples (-0.58) and oils & fats (-0.51), is less price elastic, whereas FAFH demand is the most price-responsive (-1.00). Disaggregation reveals greater price responsiveness at finer food group levels, likely reflecting higher substitution potential.

A key finding is that income elasticities are not static. They evolve with sociodemographic characteristics like income growth, urbanization, and population aging. Our projections illustrate this dynamism. For instance, under the "Middle of the road" scenario of the Shared Socioeconomic Pathways, reflecting a

[2]Uncompensated (Marshallian) elasticities measure the effect of a price change for one good while keeping household income and the prices of other goods constant, thereby reflecting both income and substitution effects. In contrast, compensated (Hicksian) elasticities measure the effect of a price change for one good while holding consumer utility constant, assuming that any price change is offset by household income adjustments to maintain the same utility level, thus excluding income effects. Both are included in our meta-sample and meta-regression analysis. However, we include a dummy to distinguish between the two types as they capture different demand responses to price changes and cannot be treated as equivalent.

continuation of historical trends as well as moderate progress towards sustainable development goals, we project that food demand in Africa will remain highly responsive to household income growth. In contrast, demand responsiveness to income for most non-discretionary foods in other regions is projected to decline as they approach consumption saturation and face population aging.

Using these evolving elasticities leads to significantly different conclusions about future global food demand compared to assuming today's elasticities remain constant. The most striking impact is on ASF, where our demand projection for 2050 is 10.7% lower than what a static assumption would suggest. While we abstract from price changes and do not intend to provide a definitive forecast, our projection results highlight the critical importance of incorporating dynamic sociodemographic shifts into long-term food system modeling.

Many elasticity values used in global food models today can be traced back to estimates developed before 1990, such as those embedded in the U.S. Department of Agriculture (USDA)'s Static World Policy Simulation model (Roningen et al., 1991). Integrated global databases of demand elasticities are rare and often outdated. For example, the USDA Commodity and Food Elasticities database,[3] which covers elasticity estimates from 1979 to 2005, is no longer maintained. Similarly, the International Evidence on Food Consumption Patterns report, which provides estimated income and price elasticities across more than 100 countries using International Comparison Program data, was last updated in 2011 (Muhammad et al., 2011). Recently, the International Food Policy Research Institute (IFPRI) has started to close this gap by periodically estimating income and price elasticities for a wide range of developing countries using harmonized food demand system estimations and representative household survey data as they become available (Income and Price Elasticities of Food Demand (E-FooD) dataset) (Ecker and Comstock, 2021). Our contribution complements these efforts. We compile the most comprehensive and up-to-date global dataset of income and price elasticity estimates published in the peer-reviewed literature (1974-2022). Our scope extends beyond LMIC, enabling meta-analytic identification of patterns in elasticity variation across settings, data, methods, and food types.

Given the heterogeneity in data sources and estimation methods, meta-analytic synthesis can offer more robust and policy-relevant elasticity estimates for use in general and partial equilibrium models. To our knowledge, we present the first predicted income elasticities by world region for nine disaggregated food

[3]U.S. Department of Agriculture, Economic Research Service. Commodity and Food Elasticities (Accessed 22 January 2025).

groups, defined in alignment with global dietary guidelines.[4] Our study also updates Green et al. (2013)'s global meta-estimates for price elasticities.[5]

Previous studies have investigated the influence of the choice of data and methods on elasticity estimates using meta-regression analysis, including Gallet (2010) and Bouyssou et al. (2024) for ASF, Chen et al. (2016) and Colen et al. (2018) for all types of food in China and Africa, respectively, and globally for price elasticities only by Cornelsen et al. (2016). Our analysis covers a longer and more recent period and incorporates more studies and estimates. This allows us to include additional variables characterizing the data and estimation methods, and interact disaggregated food groups with socio-demographic variables in our meta-regressions. This enhances our understanding of demand heterogeneity and improves the specificity of predicted elasticities across food groups.

Our study contributes to the empirical literature testing theory-based demand predictions. Support for Engel's Law corroborates earlier empirical evidence (Banks et al., 1997; Cranfield et al., 1998). The weaker patterns in support for Bennett's Law align with recent findings from Bellemare et al. (2024), who leverage data from randomized evaluations of five conditional cash transfer programs in Mexico, Nicaragua, the Philippines, and Uganda. They show that with additional income, poor households tend to shift from coarse to fine staples and coarse staples to protein, but find no evidence of substitution from staples to protein overall, nor fine staples to protein. A limitation of our analysis is that we cannot assess substitution patterns within narrowly defined food groups (e.g., between coarse and fine cereals, or by quality tiers within a category). This reflects a common constraint in meta-analyses, where food group definitions vary across primary studies and results must be harmonized to a common set of aggregated categories. The relationship between income distribution and food demand has received limited empirical attention. Cirera and Masset (2010) review the theoretical literature and argue that within-country income inequality is unlikely to substantially affect aggregate food demand. Our findings that Gini coefficients have no statistically significant effect on demand elasticities provide empirical support for their conclusion.

Finally, we contribute to the literature projecting global food demand by emphasizing the importance of

[4] Other meta-analyses of income elasticities have either covered only a specific region, e.g., Africa (Colen et al., 2018), or specific food groups, e.g., animal-sourced foods (Bouyssou et al., 2024), or focused on income-calorie and income-nutrient elasticities (Bouis and Haddad, 1992; Zhou and Yu, 2014). In addition to animal-sourced foods, Bouyssou et al. (2024) provides predicted elasticities for four food groups (fats, grains, fruits vegetables pulses and tubers, and other foods). These groups are overly aggregated, limiting their use as parameters in general or partial equilibrium models.

[5] To our knowledge, Green et al. (2013) represents the latest and only available study to date.

accounting for the impact of shifts in sociodemographic structure on future demand elasticities (Fukase and Martin, 2020; Gouel and Guimbard, 2019). Our projected elasticities, along with our meta-sample dataset and meta-elasticity estimates, provide a globally harmonized, empirically grounded resource to support improved food demand projections and enhanced food system and policy modeling.

The remainder of this paper is organized as follows. Section 2 describes the systematic review protocol and the meta-sample. Section 3 outlines the empirical strategy, including the meta-regression framework, the estimation of predicted elasticities, and the projection of global food demand to 2050. Section 4 presents the main results along with sensitivity tests. Section 5 discusses the findings and their implications and concludes.

2 Systematic literature review and descriptive statistics

We built our meta-sample following the PRISMA guidelines (Page et al., 2021a,b). Candidate primary studies were identified by conducting an exact keyword search for publication titles, abstracts, and keywords using the terms "food" and "demand", along with "elasticities" or "elasticity" through the ISI Web of Science platform and Google Scholar. Search engines considered in other food demand meta-analyses, such as AgEcon, EconLit, Medline, or RePEc (Green et al., 2013; Chen et al., 2016; Colen et al., 2018), led to similar results. Only peer-reviewed journal articles were considered. Database searches were performed as of 27 September 2022. The time frame of the studies was restricted by the earliest available year for the Science Citation Index on the Web of Science platform and encompassed 1974 to 2022. After removing duplicates, 557 candidate studies were identified.

Two members of the research team independently conducted a two-step screening process. We considered a paper eligible if both authors agreed to include it. In the case of a disagreement, a third author conducted a full-text review and made the final decision. The first step of the screening process consisted of excluding non-English text studies.[6] The second step screened the abstracts for the provision of own-calculated estimates

[6] Page et al. (2021c) suggest including non-English text studies to minimize the risk of bias. However, our search revealed less than 1% of non-English text studies.

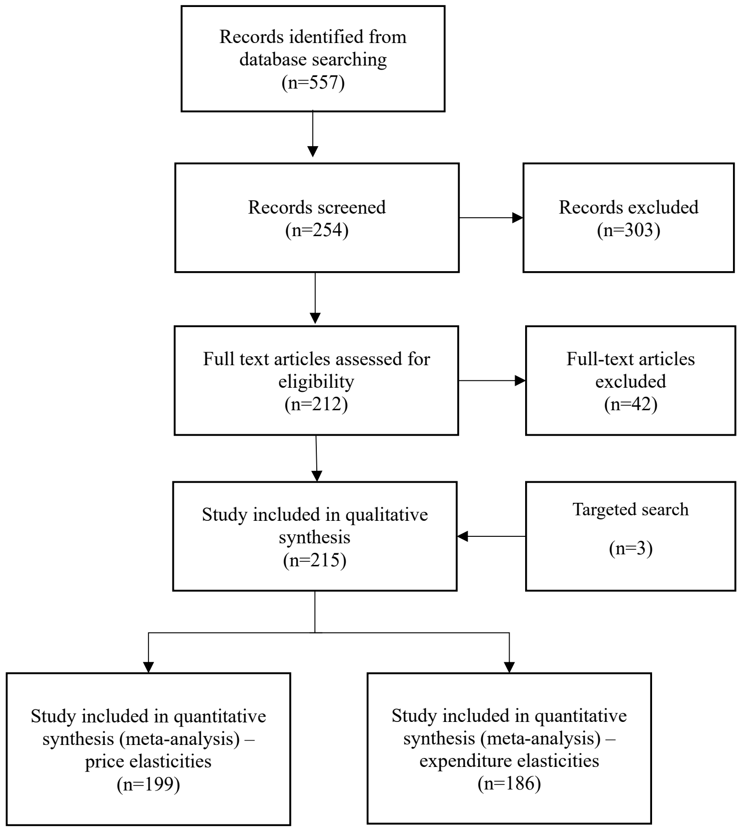

Figure 1. **PRISMA flow diagram for selection of primary studies.**

of food demand elasticities, rather than predicted or projected. This process resulted in 254 included studies. At this stage, a final screening step took place to remove 42 papers that we deemed ineligible for not reporting the sample size or not containing enough information to infer it.[7] Finally, we supplemented our meta-sample with three studies that we had pre-identified from prior reviews and our expertise.[8] The final sample covers 215 articles. Figure 1 illustrates this process and Appendix A lists the primary studies included in the meta-sample.

For each study, we collected the names of the first four authors, title, year, and journal of publication. Regarding the estimates of interest, we included the income elasticity of demand and the own-price elasticity

[7]Out of these 42 papers, Harding and Lovenheim (2017) was specifically not included because its sample size (34.2 million observations, approximately 30 times larger than the second largest sample size in the meta-sample) would significantly drive the meta-regression results given our approach using the square root of the sample size as sampling weight to address heteroskedasticity. A sensitivity meta-regression analysis including this study yields consistent results and is available upon request.

[8]The three studies added at this stage are: Zhen et al. (2014), McCullough et al. (2022), and Headey et al. (2023).

of demand.[9] There was significant heterogeneity in the aggregation of food types for these estimates. Figure B1 illustrates our re-aggregation scheme. It consists of nine food groups (Level 1) as typically defined by dietary guidelines (Herforth et al., 2019). These include: animal-sourced foods (ASF); beans, lentils, peas & soy; condiments & sweeteners; fruits, vegetables, and nuts (FV&N); grains & starchy staples; processed meals & snacks; oils & fats; food away from home (FAFH); and all beverages. Further disaggregation for some groups is reported in our database (Level 2 and Level 3). These are not included in the meta-regression analyses, the predicted elasticities, or the projections presented in this paper, as the main analysis focuses on Level 1 food groups.

In the database, we gathered variables describing the data used to estimate elasticities. These include the sample size, the structure of the data (i.e., cross-sectional, time series, or panel data), the level of representativeness (e.g., national, subnational), and the country and the year (or multiple years) in which the data were collected. We further computed the average year of data collection. Many studies report elasticity estimates by subsample (e.g., rural vs. urban, over a given subsample period). Thus, we compiled the subsample information and estimated the corresponding sample size (if missing) for each elasticity observation.

We constructed several model variables to capture key features of each elasticity estimate. These include the functional form (e.g., single-equation or demand system), the specific demand model used (e.g., AIDS, QUAIDS), the number of estimation stages, the type of demand (conditional or unconditional), the income measure (total expenditure or household income), and whether the price elasticity estimate is compensated or uncompensated. We coded whether the specification controlled for demographics to account for preference heterogeneity. In addition, we identified whether the estimation addressed common empirical challenges such as censored demand and endogeneity in prices or total expenditure.

To enrich this dataset, we added external information on countries' sociodemographic characteristics. We retrieved data on per capita GDP, population by age, and the share of the population living in urban areas from the World Bank.[10] National-level Gini indices were drawn from the World Institute for Development Economics Research to capture income inequality.[11] These external variables were merged with each

[9]This analysis does not include cross-price elasticities. In this study, price elasticities only refer to own-price elasticities.
[10]World Bank. World Development Indicators, 2024 (Accessed 18 September 2024).
[11]United Nations University, World Institute for Development Economics Research. The World Income Inequality Database - WIID, Companion dataset, 2025 (Accessed 20 May 2025).

observation for the average year of data collection linked with the elasticity estimate.[12]

The final meta-sample covers 57 countries and includes 6,572 income elasticity estimates and 6,701 price elasticity estimates. Figure B2 shows the geographic distribution of studies included in the meta-sample. The United States (46 studies) and China (26 studies) are the most represented countries. Central Africa, North Africa, West Africa (except Nigeria), the Middle East, and Eastern Europe are underrepresented. In the rest of the analysis, countries are grouped into four regions: Africa, the Americas, Asia-Oceania, and Europe.[13]

Figure 2 presents the density distributions for the elasticity estimates by food group.[14] For income elasticities, the shaded areas indicate if the goods are estimated to be inferior (negative), normal (between zero and one), or luxury goods (above one). The mean value of the distribution is between zero and one for all food groups. Unsurprisingly, it is closest to one for the most discretionary or 'luxurious' food groups, i.e., ASF (0.97) and FAFH (0.97). It is lowest for grains & starchy staples (0.59), which are considered necessities in many settings. Regarding price elasticities, most estimates fall within the $[-2, 0]$ interval, with predominantly price-inelastic demand (i.e., estimates greater than -1). The mean value of the distribution is below -1 only for FAFH and beverages (i.e., price-elastic demand), which represent mostly non-essential goods. It is the lowest in absolute value for oils & fats (-0.62). It should be noted that the price elasticity density functions include both uncompensated and compensated elasticities. The former reflects both income and substitution effects, while the latter isolates the substitution effect by holding utility constant.

Table 1 summarizes the coverage of our meta-sample by food group and type of demand elasticity. The ASF group represents 37.6% of income elasticity observations and 36.7% of price elasticity observations, followed by FV&N with 19.0% and 17.8%, respectively, and grains & starchy staples with 16.9% and 17.2%, respectively. The least represented food groups are All foods with 1.4% and 1.1% and FAFH with

[12]The average year of data collection was calculated by truncating the average value between the first and the last year of data collection in the original study. Two studies lacked information on the period of study data. For these, we assumed the average year of data collection to be 5 years before the publication year of the study. For countries for which the GDP per capita series started after 1960 (the earliest average year of data collection in the meta-sample), we imputed the value from the first non-missing year. This was the case for 7.1% and 5.8% of income and price elasticity observations, respectively. We followed the same strategy to impute missing values for the Gini index (27.0% and 32.2% of income and price elasticity observations, respectively). Sensitivity meta-regression analyses using only non-imputed data as well as other sources for Gini indices, including the World Bank's Poverty and Inequality Platform and World Development Indicators (Accessed 16 April 2025), yield consistent results and are available upon request.

[13]This grouping is selected due to the limited number of income elasticity observations in the Oceania continent (32 observations) and the South American continent (68 observations) in the meta-sample.

[14]Table B2 additionally presents descriptive statistics for the elasticity estimates for Level 2 and Level 3 food groups.

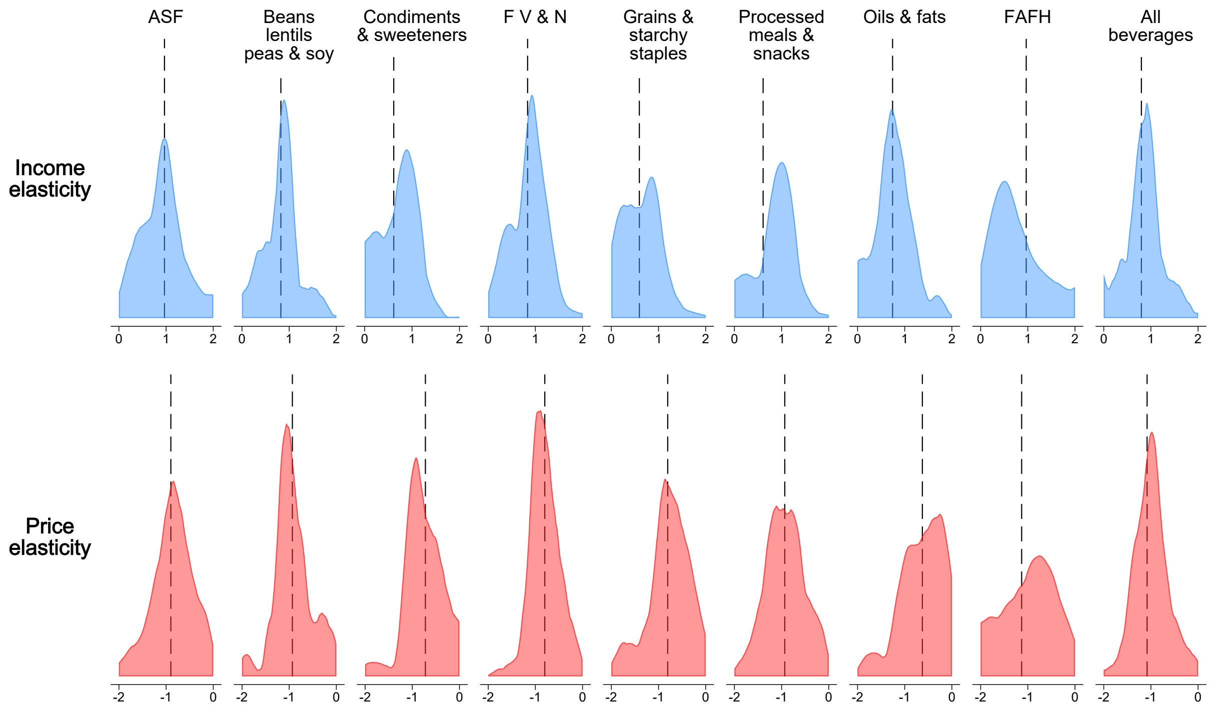

Figure 2. **Density distributions of the elasticities by food group.** Based on the full sample. The vertical dotted line represents the mean value of the distribution. Price elasticity density functions include both uncompensated and compensated elasticities. ASF: animal-sourced foods; FAFH: food away from home; FV&N: fruits, vegetables, and nuts.

2.1% and 0.5%, respectively. Table 1 also provides a summary of the descriptive statistics for the elasticity estimates. There are considerable differences in the magnitude of the income and price elasticities across regions. The average income elasticity is the smallest in the Americas, while it is the largest in Europe. The average price elasticity is the smallest in absolute terms in Asia-Oceania, while it is the largest in the Americas. The Americas is the least represented region in the meta-sample.[15] More than three out of four elasticity observations are based on data collected this century. The large majority of estimates are based on a subsample of nationally representative data and cross-sectional household-level data and use a quadratic almost ideal demand system (QUAIDS, 48% for income elasticity and 44% for price elasticity) or an almost ideal demand system (AIDS, 23% and 31%, respectively). The meta-sample is approximately evenly split between conditional and unconditional demand estimates (49% and 59% of income and price elasticity

[15] South America and Oceania are the least represented subregions in the meta-sample.

estimates are conditional, respectively) and between censored and uncensored demand (40% and 46% of income and price elasticity estimates are derived from censored demand, respectively). Most observations are estimated using a single-stage model and do not account for expenditure or price endogeneity, but control for demographics. In most cases, household income is proxied using total expenditure (74%) and price elasticities are uncompensated (78%).

Table 2 additionally presents descriptive statistics for the continuous data variables. Sample size varies greatly, ranging from only five to more than 1.1 million observations. Studies based on homescan or retail scanner panel datasets tend to have significantly larger sample sizes than studies based on time series or cross-sectional data. Regarding external variables, we observe a significant dispersion in GDP per capita, ranging from \$419 to \$51,457,[16] and in the Gini index, ranging from 20% to 67%. The mean of the share of the population below 15 years old is 28% and 8% above 64 years old. On average, approximately half of the population in the sample countries lives in an urban area with a population dependency ratio of 0.6.

[16]GDP per capita in constant 2005 purchasing power parity international dollars to match the GDP per capita data used in Shared Socioeconomic Pathways projections (Dellink et al., 2017; Crespo Cuaresma, 2017; Leimbach et al., 2017).

	Income elasticity				Price elasticity			
	N	Share	Mean	Sd	N	Share	Mean	Sd
Food group								
All foods	89	0.014	0.739	0.296	72	0.011	-0.685	0.209
ASF	2,468	0.376	0.966	0.633	2,452	0.366	-0.899	0.752
Beans lentils peas & soy	166	0.025	0.824	0.686	171	0.026	-0.932	0.898
Condiments & sweeteners	263	0.040	0.615	0.759	293	0.044	-0.722	0.655
F V & N	1,247	0.190	0.835	0.491	1,191	0.178	-0.801	0.415
Grains & starchy staples	1,110	0.169	0.594	0.594	1,151	0.172	-0.804	0.740
Processed meals & snacks	204	0.031	0.608	0.775	309	0.046	-0.933	0.641
Oils & fats	420	0.064	0.743	0.437	463	0.069	-0.626	0.508
FAFH	137	0.021	0.966	0.836	33	0.005	-1.130	0.669
All beverages	468	0.071	0.798	0.488	566	0.084	-1.081	0.625
Region								
Africa	1,643	0.250	0.850	0.568	1,680	0.251	-0.886	0.545
Americas	783	0.119	0.546	0.712	1,116	0.167	-0.893	0.855
Asia-Oceania	2,615	0.398	0.859	0.656	2,482	0.370	-0.813	0.729
Europe	1,531	0.233	0.863	0.473	1,423	0.212	-0.863	0.534
Sample type								
All	1,904	0.290	0.732	0.688	2,412	0.360	-0.810	0.738
Subsample	4,668	0.710	0.856	0.574	4,289	0.640	-0.881	0.634
Structure of data								
Cross-sec. & TS	4,787	0.728	0.854	0.583	4,692	0.700	-0.852	0.712
Panel data	1,785	0.272	0.730	0.676	2,009	0.300	-0.863	0.575
Data representativeness								
National	5,297	0.806	0.833	0.606	5,805	0.866	-0.864	0.662
Subnational	1,275	0.194	0.766	0.634	896	0.134	-0.800	0.745
Data period								
Pre-2000	1,516	0.231	0.706	0.715	1,534	0.229	-0.706	0.835
2001-2010	2,644	0.402	0.794	0.604	2,704	0.404	-0.930	0.628
2011-2020	2,412	0.367	0.921	0.531	2,463	0.368	-0.866	0.592
Type of conditionality								
Conditional	3,234	0.492	0.970	0.575	3,978	0.594	-0.862	0.701
Unconditional	3,338	0.508	0.676	0.613	2,723	0.406	-0.845	0.633
Demand model								
Single-equation	801	0.122	0.581	0.501	258	0.039	-0.793	0.860
AIDS type	1,478	0.225	0.883	0.580	2,106	0.314	-0.891	0.782
QUAIDS type	3,119	0.475	0.930	0.624	2,969	0.443	-0.837	0.585
Other	1,174	0.179	0.613	0.591	1,368	0.204	-0.852	0.633
Censored demand								
No	3,922	0.597	0.783	0.627	3,590	0.536	-0.811	0.639
Yes	2,650	0.403	0.876	0.586	3,111	0.464	-0.906	0.710
Number of estimation stages								
Single-stage	4,065	0.619	0.849	0.589	4,224	0.630	-0.855	0.705
Multi-stage	2,507	0.381	0.774	0.646	2,477	0.370	-0.855	0.619
Account for exp. endogeneity								
No	5,013	0.763	0.790	0.575	5,276	0.787	-0.841	0.677
Yes	1,559	0.237	0.916	0.710	1,425	0.213	-0.909	0.663
Account for price endogeneity								
No	5,857	0.891	0.812	0.631	5,818	0.868	-0.826	0.702
Yes	715	0.109	0.885	0.428	883	0.132	-1.049	0.398
Control demographics								
No	1,452	0.221	0.499	0.629	1,093	0.163	-0.683	0.822
Yes	5,120	0.779	0.911	0.576	5,608	0.837	-0.889	0.636
Income elasticity measure								
Income	1,737	0.264	0.708	0.581	-	-	-	-
Total expenditure	4,835	0.736	0.861	0.618	-	-	-	-

	Income elasticity				Price elasticity			
	N	Share	Mean	Sd	N	Share	Mean	Sd
Uncompensated or compensated demand								
Compensated	-	-	-	-	1,487	0.222	-0.771	0.647
Uncompensated	-	-	-	-	5,214	0.778	-0.879	0.680
Total	**6,572**	**1.000**	**0.820**	**0.612**	**6,701**	**1.000**	**-0.855**	**0.674**

Table 1. **Descriptive statistics of data and model variables included in the meta-sample.** Subnational also includes non-representative data. TS: time series. N: number. AIDS: Almost Ideal Demand System; QUAIDS: Quadratic Almost Ideal Demand System.

	Income elasticity				Price elasticity			
	min	mean	max	sd	min	mean	max	sd
Sample size	5	16,720	1,152,528	84,437	10	31,595	1,152,528	108,022
GDP per capita (2005 PPP)	419	12,411	46,778	12,753	419	14,230	51,457	13,925
Urbanization (%)	0.150	0.495	1.000	0.217	0.131	0.529	1.000	0.231
Population >64 yo	0.015	0.083	0.211	0.051	0.015	0.084	0.211	0.052
Population <15 yo	0.135	0.283	0.508	0.109	0.135	0.289	0.508	0.111
Population dependency ratio	0.355	0.598	1.122	0.194	0.355	0.614	1.122	0.193
Gini index	0.199	0.382	0.670	0.053	0.220	0.385	0.670	0.057

Table 2. **Descriptive statistics of the sociodemographic and continuous variables.** PPP: purchasing power parity international dollars. yo: years old.

3 Estimation and projection methods

3.1 Meta-regression

We estimate separate meta-regressions to analyze the relationship between household income and food demand and between prices and food demand. The model can be described as follows:

$$\begin{aligned}\epsilon_{i,s,j} = \beta_0 + \sum_m \beta_m F_{m,i} + \sum_n \beta_n D_{n,s,j} + \sum_p \beta_p M_{p,i,s,j} + \sum_q \beta_q S_{q,s,j} \\ + \sum_m \sum_q \beta_{m,q} F_{m,i} \times S_{q,s,j} + \gamma \frac{1}{\sqrt{N_{s,j}}} + \upsilon_j + \nu_s + \varepsilon_{i,s,j}\end{aligned} \tag{1}$$

$\epsilon_{i,s,j}$ is the elasticity estimate for food item i for sample s in study j. $F_{m,i}$, $D_{n,s,j}$, $M_{p,i,s,j}$, and $S_{q,s,j}$ are the m food group dummies (Level 1) and the n, p, and q variables that contain the data, model, and sociodemographic attributes for estimate $\epsilon_{i,s,j}$. β_m, β_n, β_p, β_q, and $\beta_{m,q}$ represent the coefficients of interest and quantify the impact of each of these attributes. $\varepsilon_{i,s,j}$ is the error term.[17]

This two-level random intercept model is estimated via maximum likelihood. It accounts for random effects at two hierarchical levels: the study υ_j (the higher level) and the sample ν_s (the lower level). By doing so, it allows for further random variation within samples (e.g., national, rural only, subsample period). This model is preferred over pooled OLS as it controls for possible study-specific and sample-specific unobserved heterogeneity (i.e., it accounts for between- and within-study variation). This specification is also favored relative to fixed effects. A fixed effects estimator would control for within-study unobserved heterogeneity. However, many covariates in our model only exhibit between-study variation, thus random effects are more appropriate.

We perform Egger et al. (1997)'s test for publication bias involving regressing elasticity estimates on an inverse indicator of their precision. Publication bias may arise given the likely preference for statistically significant and theory-consistent empirical results among research outputs (Stanley and Doucouliagos, 2014). The first-best indicator of precision is the standard errors of elasticity estimates. However, only around one-third of papers reported standard errors, and half reported the significance levels of estimates. Solely including studies reporting standard errors or significance levels may bias the meta-sample, as these studies

[17] It was not possible to include additional interaction terms (e.g., between food groups and regions) due to singularity issues. In addition, interaction terms consume degrees of freedom (i.e., number of studies minus the number of parameters estimated), leaving fewer to assess variability across studies in our two-level random intercept model.

could be more likely to report statistically significant estimates. As a consequence, we use the inverse square root of the sample size as an indicator of study precision, relying on the correlation between sample sizes and t-statistics.[18] The Egger test shows the presence of publication bias in our meta-sample (Table B3). As a result, we include the inverse square root of the sample size $\frac{1}{\sqrt{N_{s,j}}}$ as an additional regressor in our meta-regression model (Stanley and Doucouliagos, 2014).

We allow for heteroskedasticity using robust clustered standard errors at the study level. This addresses potential violations of the independence assumption, as estimates within the same study are likely correlated. In addition, we apply the square root of the sample size (as a proxy for study standard errors) as a sampling weight to address heteroskedasticity arising from the variance of the elasticity estimates differing across studies and between samples (Card and Krueger, 1995). Table B4 shows the relevance of this approach as larger sample sizes are a strong predictor of a higher significance level for elasticity estimates.

The variables included in the main meta-regression specification are summarized in Table B1. We include a control variable indicating whether the elasticity estimate is derived from the full sample or a subsample. This accounts for systematic differences in consumption behavior and elasticities that may arise due to sample composition. For instance, elasticities estimated from more homogeneous subsamples may differ in magnitude and direction compared to those based on nationally representative samples. Most elasticity estimates in the meta-sample are based on nationally representative data (81% for income and 87% for price elasticities) (Table 1). Owing to this limited variation, we omit the national vs. subnational distinction from the main specification. While the data period may capture global dietary preference shifts, this variable is excluded due to multicollinearity with other covariates.[19]

Regarding the model variables, we emphasize key structural choices such as whether a single-equation model or a demand system is used, the type of demand system, and the type of conditionality (conditional vs. unconditional demand), as these reflect decisions from the econometrician. We also distinguish between income elasticities estimated using total expenditure as a proxy for household income and between compensated and uncompensated price elasticities, as they capture different behavioral responses to price changes. Failing to distinguish between the latter would conflate conceptually distinct measures and introduce unnec-

[18] Table B4 shows that larger sample sizes are a strong predictor of a higher significance level for elasticity estimates in our meta-sample.

[19] This is because certain model choices, access to new data sources (e.g., scanner data), or sociodemographic indicators (e.g., per capita GDP) may evolve over time.

essary heterogeneity into the meta-regressions. Other potentially secondary model characteristics —such as the data structure (e.g., panel data, time series, cross-sectional data), whether the study accounts for censored demand, the number of estimation stages, whether it corrects for endogeneity in total expenditure or prices, and whether it includes demographic controls —are excluded from the main model specification for parsimony and because of their limited variation across studies (Table 1). We show the robustness of our meta-regression results to the inclusion of these secondary data and model variables in Table D1.

Per capita GDP is used to examine how real income affects food consumption. It allows us to empirically test Engel's Law, which states that as household income increases, the share of income spent on food declines (Engel, 1857). It also enables us to test Bennett's Law, which suggests that rising household income leads to a shift away from coarse, calorie-dense staples toward finer staples, animal-sourced foods, and more diverse diets (Bennett, 1941). Our main model specification includes the level of urbanization, as it may influence food consumption patterns through differences in the type of labor and income, the opportunity cost of time, or proximity to agricultural production and marketplaces (Regmi and Dyck, 2001). Information on demographics can also be indicative of the caloric and nutritional needs or food preferences of different age groups. Demographic changes represent a significant source of aggregation bias (Blundell and Stoker, 2005). In demand theory, the aggregation problem refers to the capacity to transition from micro- to macro-economics and represent all households' demand at one point in time. Given the significant global population aging trend (Lutz et al., 2008), we specifically include the share of the population aged 65 or above. Life-cycle theory predicts consumption smoothing and declining marginal propensities to consume with age (Gourinchas and Parker, 2002). Older individuals are expected to have more stable and habitual consumption patterns, which could induce flatter Engel curves. Finally, our main model specification includes geographical regions. This is motivated by the significant heterogeneity in estimates observed between regions.[20]

We further explore alternative specifications. First, we control for income inequality using the Gini index, as the distribution of income may influence aggregate food demand patterns and elasticities when Engel curves are non-linear (Cirera and Masset, 2010). In such settings, an increase in inequality can lead

[20] Table B5 shows t-test statistics for equality of elasticity estimates by region. Meta-regression results are presented before and after the introduction of regional dummies, as they may be correlated with other sociodemographic variables (Table C2 and Table C3). Due to a lack of observations when splitting the sample, the stratified meta-regression models by country income group (Table C4) and for ASF, FV&N, and grains & starchy staples are not including regions (Table C5, Table C6, and Table C7).

to a reduction in total food demand, as poorer households typically have higher marginal propensities to consume food than richer peers. Second, we include the share of the population below 15 years of age. This variable may proxy household size, as a higher proportion of children typically implies larger households, which can give rise to economies of scale in food consumption. Third, we examine whether demographic structure affects demand through the population dependency ratio, given its potential association with income levels, saving behavior, and household consumption dynamics. We define this ratio as the combined share of individuals below 15 and above 64 years old.

Using the meta-regression results from our main specification, we estimate predicted elasticities for Level 1 food groups by region. Data and model covariates are set to their sample means. For socio-economic variables, the values for each region are the weighted average of the 2021 values across the region's countries. Population is used as weight.[21]

3.2 Projections

This is the first review to provide meta-estimates to systematically quantify the relation between household income and demand for all main food types at the global level. We additionally shed light on differences in this relation between regions, income, demographics, and urbanization levels. To demonstrate the value of the elasticities presented in this study and the importance of these heterogeneities, we estimate projected income elasticities up to 2050 based on the Shared Socioeconomic Pathways (SSPs) (Equation (2)) and compare values with constant predicted elasticities as of 2021 (O'Neill et al., 2014). SSPs outline a range of five plausible pathways for societal development, grounded in hypotheses about the key societal factors that most significantly influence the challenges of climate change mitigation and adaptation.[22] They consist of projected socioeconomic global changes, including GDP (Dellink et al., 2017; Crespo Cuaresma, 2017; Leimbach et al., 2017), urbanization (Jiang and O'Neill, 2017), total population, and population by age group

[21] We estimate the predicted elasticities' standard errors using the following expression: $se_E = \left[\mathbf{XVX'} + sd_\nu^2 + sd_\upsilon^2 + sd_\varepsilon^2\right]^{\frac{1}{2}}$. $\mathbf{X}$ represents the row vector of covariate means, including a one for the intercept. $\mathbf{V}$ is the variance-covariance matrix of the estimated coefficients. sd_ν and sd_υ are the standard deviations of the random effects. sd_ε is the standard deviation of the residuals. By including the off-diagonal elements of $\mathbf{V}$ (covariances) in the computation of the standard errors for predicted elasticity estimates, we account for the correlation between regression coefficients, improving the precision of the standard error estimates.

[22] The five pathways are: SSP1: Sustainability ("taking the green road"); SSP2: "Middle of the road"; SSP3: Regional rivalry ("a rocky road"); SSP4: Inequality ("a road divided"); and SSP5: Fossil-fueled development ("taking the highway") (O'Neill et al., 2014).

(KC and Lutz, 2017).[23]

$$\hat{\epsilon}_{i,r,t} = \hat{\beta}_0 + \sum_m \hat{\beta}_m F_{m,i} + \sum_n \hat{\beta}_n \overline{D}_n + \sum_p \hat{\beta}_p \overline{M}_{p,i} + \sum_q \beta_q \overline{S}_q^{r,t} + \sum_m \sum_q \hat{\beta}_{m,q} F_{m,i} \times \overline{S}_q^{r,t} + \hat{\gamma} \frac{1}{\sqrt{\overline{N}}} \tag{2}$$

where $\overline{D}$ and $\overline{M}$ represent the sample mean of the data and methods variables, respectively. $\overline{N}$ is the sample mean of the sample size. $\overline{S}^{r,t}$ is the population-weighted average for the sociodemographic variables for region r, based on the projected population for each country at time t.

Using our projected income elasticity estimates, we simulate global food demand up to 2050. Baseline national-level food consumption is proxied using the Food and Agriculture Organization (FAO) data on food availability in 2021.[24] This dataset provides the annual total food supply (in tons) for each country and has been shown to correlate with other indicators of food intake and health outcomes (Naska et al., 2008). We focus on the following food groups: ASF; beans, lentils, peas & soy; condiments & sweeteners; FV&N; grains & starchy staples; and oils & fats.[25] Several models of food and agricultural markets have been used in the literature to project global trends, such as IFPRI's IMPACT (International Model for Policy Analysis of Agricultural Commodities and Trade) or the OECD-FAO AGLINK-COSIMO model (Rosegrant and The IMPACT Development Team, 2012; OECD and Food and Agriculture Organization, 2022). Generally, these models assume that demand elasticities remain constant over time. In this application, we demonstrate that allowing demand parameters to vary with projected socio-economic variables may significantly influence projection results.

$$\hat{f}_{i,r,t} = \frac{f_{i,r,2021}}{p_{r,2021}} \times p_{r,t} \times g_{r,t-2021}^{\hat{\epsilon}_{i,r,t}} \tag{3}$$

In this projection exercise, GDP per capita growth ($g_{r,t-2021}$, as the ratio of GDP per capita in future year t over GDP per capita in 2021) is used to proxy changes in real income at the population level. $p_{r,t}$ is the

[23]The SSP projection data is extracted from the International Institute for Applied Systems Analysis (IIASA)'s SSP Database - Version 2.0, 2018 (Accessed 18 October 2024). When various models (IIASA, OECD, and PIK) are available for a given SSP scenario, year, and outcome, we take the average between the available models.

[24]Food and Agriculture Organization. FAOSTAT. Food balance sheets, 2022 (Accessed 13 January 2025).

[25]FAO's Food balance sheet data is not available for processed meals & snacks, FAFH, and all beverages. Table C15 provides details for regrouping FAO commodities.

regional population for year t. $\hat{f}_{i,r,t}$ and $\hat{\epsilon}_{i,r,t}$ represent the estimated projected demand and the estimated projected income elasticity for food group i in region r in future year t, respectively. While prices are an important determinant of food demand, we abstract from price changes. This is motivated by our focus on long-run structural shifts in income-driven demand and by the considerable uncertainty surrounding long-term global food price forecasts. The goal is not to predict market-equilibrium outcomes, but to highlight how projected changes in sociodemographic and elasticity structures may shape future consumption patterns.

4 Results

4.1 Meta-regression

Table 3 provides the estimated coefficients for the meta-regression analysis for each elasticity type.[26,27] Our results indicate that using a demand system rather than a single-equation model does not significantly affect elasticity estimates. However, the specific type of demand system does matter. In particular, QUAIDS-type models are associated with lower income elasticity estimates compared to AIDS-type models. This likely reflects QUAIDS' ability to flexibly capture nonlinearities in Engel curves, particularly the diminishing marginal responsiveness of food demand at higher income levels, as motivated by Banks et al. (1997). In contrast, alternative demand systems grouped under "Other" (e.g., exact affine stone index (EASI), translog, Rotterdam) do not exhibit systematic differences relative to AIDS-type models.[28] Income elasticities estimated conditional on food demand or the demand for a higher-aggregate food category are associated with higher values. This is consistent with economic intuition, where spending patterns respond more strongly

[26] Table C1 displays the meta-regression analysis results with all coefficients, including the food group dummies and their interactions with sociodemographic variables. Table C2 and Table C3 present the meta-regression analysis results with stepwise introduction of variables.

[27] The conditional R^2 represents the proportion of variance explained by both the independent variables and the random effects. It is estimated as follows: $R^2 = \frac{sd_f^2+sd_\nu^2+sd_\upsilon^2}{sd_f^2+sd_\nu^2+sd_\upsilon^2+sd_\varepsilon^2}$. sd_f^2 represents the variance explained by the fixed effects (i.e., the independent variables, without considering random effects), sd_ν^2 and sd_υ^2 the between-group variances (i.e., variance explained by the random effects), and sd_ε^2 the residual (within-group) variance.

[28] In robustness checks, we further disaggregated the "Other" category to isolate EASI-type models, which represent higher-order flexibility systems than QUAIDS (Lewbel and Pendakur, 2009). We found a negative, though not statistically significant, difference in income elasticity estimates between EASI and AIDS models; however, this comparison may suffer from limited statistical power, as only 7.5% of income elasticity observations in our sample are based on EASI-type models. Results are available upon request.

once a baseline demand for food or broad categories is already established. Using household income rather than total expenditure to measure income elasticities leads to lower estimates. This corroborates prior evidence suggesting that household income is measured with greater error, introducing attenuation bias, and may poorly reflect the permanent consumption capacity of households compared to total expenditure (Bhalla, 1979). Column (2) of Table D1 provides results for a sensitivity analysis in which we add the extra data and model variables discussed in Section 3.1 and presented in Table B1. Findings indicate no statistically significant effects on income elasticity estimates.

In Table C4, we disaggregate the sample by country income group, distinguishing between LMIC and high-income countries (HIC).[29] The results suggest that measuring income elasticities using household income instead of total expenditure has a negative effect in LMIC but a positive effect in HIC. In LMIC, household income is more volatile, frequently under-reported, or missing in household surveys, making total expenditure a more reliable proxy for permanent household income (Carletto et al., 2021). Rural households in these settings often smooth consumption through in-kind transfers, remittances, or savings (Combes and Ebeke, 2011). Consequently, using reported household income introduces measurement error that attenuates elasticity estimates. Given that food represents a large share of household budgets in LMIC, this results in steeper Engel curves when using expenditure. In contrast, household income tends to be more stable and accurately reported in HIC, while food constitutes a smaller share of the household budget. Expenditure may be less sensitive to short-term income fluctuations due to access to credit, habit persistence, and intertemporal smoothing. In this context, income variation is more likely to reflect permanent differences in living standards, which may lead to higher estimated elasticities. As a result, Engel curves estimated using household income may be steeper.

[29] Country income classifications are based on gross national income (GNI) per capita thresholds defined by the World Bank in 1987—the first year such rankings were published—closely aligning with the start of our meta-sample. Source: World Bank, GNI per capita Operational Guidelines & Analytical Classifications (OGHIST), 2023 (Accessed 23 February 2025). LMIC include low-, lower-middle-, and upper-middle-income countries. Sensitivity checks using classifications from 2021 or continuous classifications yield consistent results and are available upon request.

	Income elasticity	Price elasticity
Data variables		
Subsample	0.001	0.064
	(0.019)	(0.056)
Model variables		
Demand system	-0.054	0.196
	(0.079)	(0.134)
Demand system × QUAIDS	-0.100***	0.008
	(0.020)	(0.010)
Demand system × Other	0.016	-0.106
	(0.033)	(0.097)
Conditional	0.249***	0.024
	(0.049)	(0.048)
Exp. measure: Income	-0.197**	
	(0.092)	
Compensated demand		0.111***
		(0.032)
Sociodemographic variables		
log(GDP pc)	-0.120**	0.212
	(0.056)	(0.421)
Urbanization	2.300***	-0.118
	(0.369)	(1.552)
Pop >64 yo	-4.399***	-4.005
	(1.452)	(6.267)
Regions		
Africa	0.355**	0.215
	(0.146)	(0.384)
Americas	-0.247**	-0.055
	(0.097)	(0.487)
Asia-Oceania	0.104	0.414
	(0.089)	(0.496)
Publication bias correction term	-0.772	0.629
	(0.708)	(1.489)
Constant	0.935**	-2.611
	(0.462)	(2.396)
N	6572	6701
Number of studies	186	199
Number of countries	54	55
Conditional R^2	0.454	0.553
Variance of error terms	0.268	0.302
Variance of random effects	0.119	0.280
Food groups	Yes	Yes
Food groups × SDV	Yes	Yes

Table 3. **Meta-regression estimates**. Reference categories are underlined in Table B1. The entire model can be found in Table C1. SDV: sociodemographic variables.
Back to Section 4.1.

Most of the estimated coefficients for the data and model variables do not have a statistically significant effect on price elasticities. This can be viewed positively, as it suggests that data characteristics or individual modeling choices do not significantly influence the estimated elasticities. One exception is for compensated elasticities, which are associated with lower absolute values than uncompensated elasticities. This was expected since most income elasticities are positive, and uncompensated elasticities incorporate both the substitution effect and the (negative) income effect, whereas compensated elasticities isolate the substitution effect. Column (5) of Table D1 shows that accounting for expenditure endogeneity, which often stems from simultaneity bias or omitted variable bias, negatively affects price elasticity estimates (increases their absolute value), though not statistically significant. Accounting for such endogeneity removes the confounding influence of household income changes that would otherwise "mask" the full substitution response. As a result, the price elasticity becomes more negative. This is in line with the demand estimation literature, which highlights the importance of correcting for expenditure endogeneity through an instrumental variable or control function approach (Banks et al., 1997; Blundell et al., 1998). Column (5) of Table D1 also shows a negative coefficient on controlling for demographics, though not statistically significant. Household characteristic differences predict consumption preferences, needs, and budget allocations. Controlling for demographic characteristics reduces the risks of omitted variable bias and better identifies substitution behavior (Pollak and Wales, 1981).

This study also examines how sociodemographic variables influence income and price elasticities. Figure 3 displays the estimated coefficients and confidence intervals for food group indicators and their interactions with sociodemographic characteristics. The reference category is 'All foods', so all estimates should be interpreted as differences relative to this group.

Based on Engel's Law, we expect the proportion of income spent on food to decrease as household income increases, even as the absolute amount spent may rise. In this study, real income at the population level is proxied by per capita GDP. Thus, we expect income elasticities to be larger when a country's per capita GDP is low, and the contrary for countries with higher incomes. Our estimates confirm this, as a 1% increase in GDP per capita is associated with a 0.0012-point decrease in income elasticity for 'All foods', holding other factors constant. The relationship between per capita GDP and income elasticities is negative for all food groups, except for ASF, condiments & sweeteners, and FAFH. This is partially in line with Bennett's Law, which states that rising income leads to a notable shift in dietary patterns characterized by a decreased reliance on coarse, calorie-dense starchy staples and increased consumption of protein, nutrient-dense, and discretionary foods. Per capita GDP has a statistically significant positive effect on the income elasticity for FAFH. The wealthier a country becomes, the greater share of additional income consumers allocate to FAFH, a discretionary food. However, per capita GDP does not have a stronger negative effect on the income elasticity for grains & starchy staples than on the elasticity for 'All foods' and has a nil effect on the income

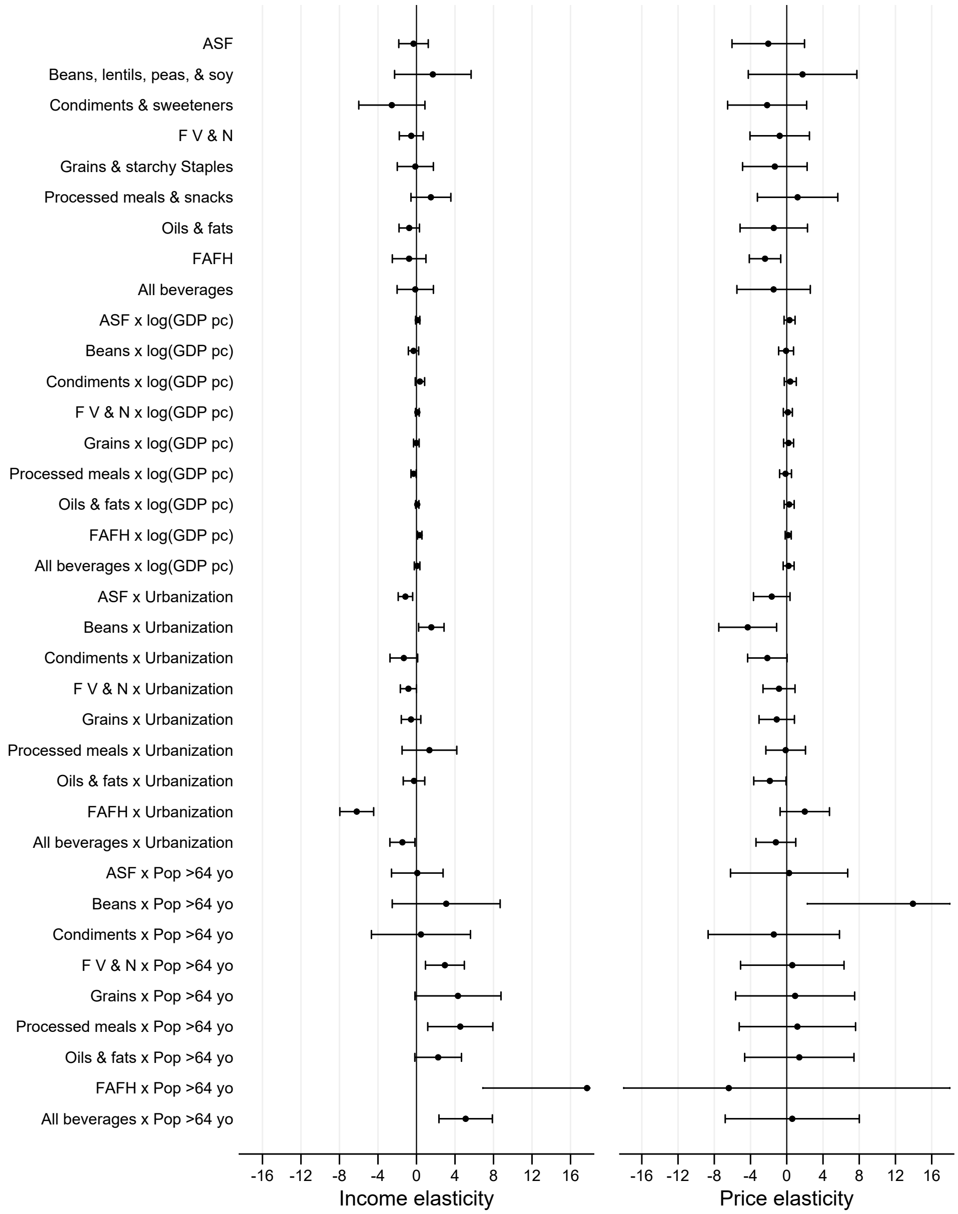

Figure 3. **Estimated effects and confidence intervals of the food group variables and their interactions with sociodemographic variables on income and price elasticities.** Reference category: All foods. Confidence intervals at the 95% level. Confidence intervals without end caps are truncated for ease of presentation.

elasticity for ASF.

A larger share of the population living in urban areas may reflect higher access to marketed food. Our findings indicate that urbanization rates have a positive effect on income elasticities. This is true for all food groups except FAFH, whose consumption is more established in urban settings (Ruel et al., 2017), limiting further increases as income rises. To explore the finding that the inclusion of urbanization in the meta-regression model reverses the sign of the coefficient on GDP per capita from positive to negative (Table C2), we incorporate an interaction term between GDP per capita and urbanization. The coefficient on the interaction term is negative and statistically significant, indicating that the effect of urbanization on food demand responsiveness to household income diminishes as income rises and that the effect of income growth on income elasticities is not uniform. Real income growth reduces income elasticity estimates in more urbanized countries but has a limited effect in low urbanization contexts (Table D3).

We find that the income elasticity of food demand declines with the share of the population 65 years old or above. This is consistent with lifecycle theory and less responsive consumption among older households. However, the interaction terms are positive for processed foods, FAFH, and beverages, suggesting that older consumers may shift toward convenience-oriented and discretionary food consumption as income rises. Finally, sensitivity analyses including the share of population below 15 years old and a Gini index to the meta-regression show no statistically significant effects (Table D3).

For price elasticities, we do not observe any statistically significant effects for the sociodemographic variables (Table 3 and Figure 3). The direction of the coefficient on per capita GDP suggests that higher income is associated with lower absolute price elasticities, which aligns with the idea that wealthier consumers are less sensitive to price changes because food represents a smaller share of their overall budget. However, Table C4 shows that a reverse relationship occurs in HIC. Food demand in such contexts may shift toward luxury or more substitutable items (e.g., organic, premium brands, eating away from home), which may have higher price elasticities. Also, substitution opportunities and market integration are higher than in LMIC. The negative association between price elasticities and urbanization is only statistically significant at the 95% level for beans, lentils, peas & soy and oils & fats. Urban diets may rely more on market purchases rather than home production. Beans and other pulses may compete more closely with other protein sources in urban areas, increasing substitution when prices rise. Greater diversity in retail formats and available substitutes can also explain these results, particularly in HIC. Finally, the share of the population aged 65 and above is negatively associated with price elasticities in LMIC. Older consumers in these settings are more sensitive to price changes, likely due to limited income sources (e.g., lack of pension coverage). In contrast, elderly households in HIC may smooth consumption or be shielded from price shocks through pensions or welfare programs.

We perform various sensitivity analyses using alternative model specifications in Appendix D. First, we show that the meta-regression analysis results are robust to the addition of a categorical data period variable in the model (columns (3) and (6) of Table D1). However, the negative and statistically significant effect of GDP per capita on income elasticities observed in the main specification is attenuated. This suggests that part of the relationship may be confounded by time-related heterogeneity in study characteristics or absorbed by the strong correlation between income levels and time. Second, the coefficient on the publication bias correction term is not statistically significant in our main specification. We find that results are robust to its exclusion (columns (2) and (5) of Table D2). Third, Figure 2 shows a large dispersion and the presence of a number of implausible values among the elasticity estimates in the meta-sample. Nevertheless, our results are robust to the exclusion of outliers, i.e., income and price elasticity estimates outside the range $[\mathrm{Q1} - 3 \times \mathrm{IQR}, \mathrm{Q3} + 3 \times \mathrm{IQR}]$ (columns (3) and (6) of Table D2). Finally, results are robust to the removal of observations with price elasticity estimates above zero, i.e., inconsistent with economic theory (column (7) of Table D2).

4.2 Predicted elasticities

Figure 4 presents the predicted income and price elasticities by food group and region.[30] As expected, income elasticities are the highest for more discretionary food groups such as ASF and FAFH, and lowest for grains & starchy staples. The findings confirm the geographical heterogeneity shown in the descriptive statistics (Table B5). Predicted income elasticities for grains & starchy staples are the highest in Africa, where they form the bulk of diets due to their affordability and caloric density. In contrast, ASF emerges as the most income-elastic category in Africa. Similarly, other food groups like FV&N and oils & fats exhibit higher elasticities in Africa than in other regions, indicating a broader shift toward dietary diversification as incomes grow. Conversely, income elasticities for ASF are lowest in Europe and the Americas, where consumption levels are high.[31] In both regions, rising incomes have enabled the average consumer to move beyond subsistence, with surplus household income now directed toward more luxurious and discretionary consumption.

Turning to price elasticities, regional and food-group variation is also evident. Demand for staple foods such as grains & starchy staples and oils & fats tends to be less price elastic, whereas FAFH demand is

[30] Table C8 provides the results in a table format. The standard errors are displayed in Table C10.
[31] Our World in Data. Per capita meat consumption by type, 2021, 2023 (Accessed 20 January 2025).

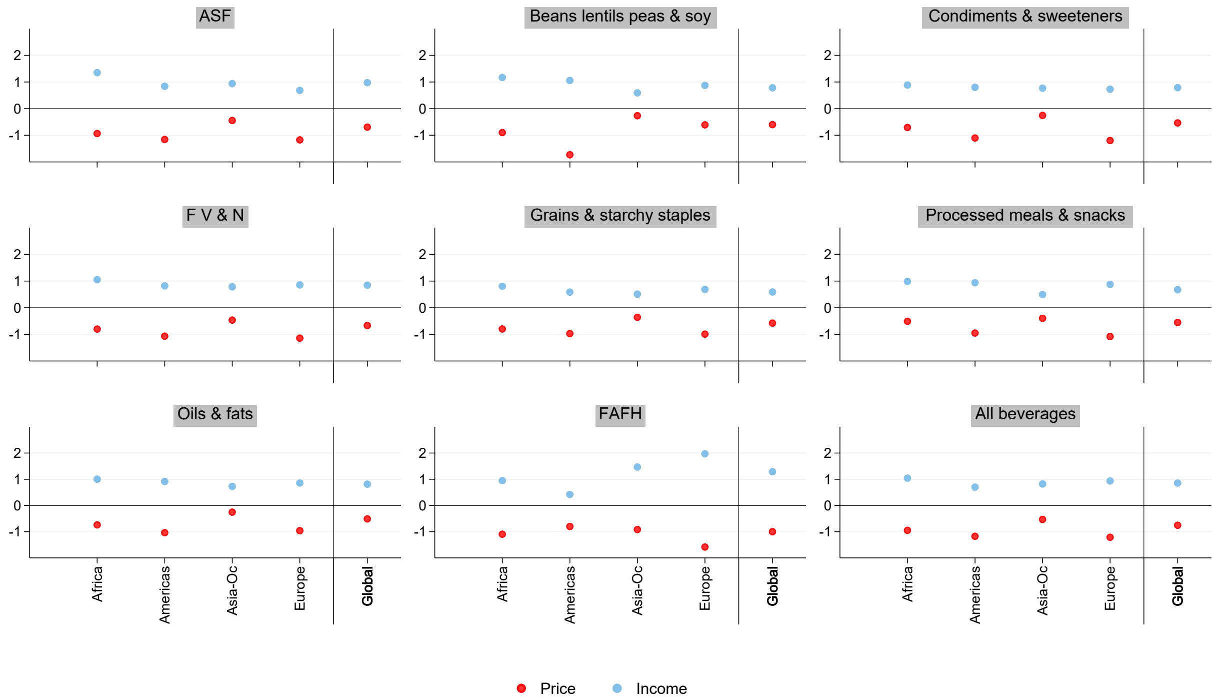

Figure 4. **Predicted income and price elasticities, by region and food groups.** Oc: Oceania. ASF: animal-sourced foods; FAFH: food away from home; FV&N: fruits, vegetables, and nuts. Results in table format can be found in Table C8. Standard errors can be found in Table C10.

the most price-responsive, being unit-elastic at the global level (a price elasticity of -1.0). This aligns with expectations, as grains & starchy staples and oils & fats are often necessities with fewer close substitutes, especially in LMIC settings. In Africa and Europe, the demand for FAFH is price elastic, while it remains inelastic in the Americas and Asia-Oceania. North America accounts for 47% of global FAFH market revenue,[32] and South America is among the fastest-growing markets in this segment (Popkin and Reardon, 2018). Meanwhile, China and India, along with the United States, dominate the global online food delivery sector.[33] Table C9 disaggregates the results for predicted uncompensated and compensated price elasticities by food group and region.[34] In line with economic theory and the meta-regression estimates, uncompensated elasticities are consistently larger in absolute value than compensated elasticities.

[32]The Brainy Insights. Food Away From Home Market, 2023 (Accessed 22 January 2025).
[33]Statista. Marketing Insights. eCommerce. Online Food Delivery, 2024 (Accessed 22 January 2025).
[34]The standard errors are available upon request.

4.3 Projections

Table C12 presents population-weighted averages of sociodemographic variables in 2021 by region, alongside SSP projections for 2050 across all scenarios. Fossil-fuel development (SSP5) leads to the highest projected GDP per capita, while regional rivalry (SSP3) yields the most limited economic growth. SSP3 is also associated with the highest projected total population and the lowest projected rates of urbanization and population aging. Total population is projected to rise least in the sustainability (SSP1) and SSP5 scenarios, while urbanization and population aging rise most. Table C13 provides a time series of projected changes in sociodemographic variables by region under SSP2 ("Middle of the Road"). This scenario is often used as a baseline in the literature, reflecting a continuation of historical trends and moderate progress toward sustainable development goals and greenhouse gas emission reductions.

Table 4 presents estimates of predicted income elasticities for 2021[35] and projections for each decade from 2030 to 2050 for SSP2 by food group and region. Results reveal divergent projected trends in income elasticities across regions, reflecting both differences in economic and sociodemographic trajectories and underlying consumption saturation. In Africa, income elasticities remain high or even increase slightly across most food groups between 2021 and 2050. This suggests that rising income and urbanization will continue to fuel growth in demand, particularly for nutrient-rich items such as beans, lentils, peas & soy (1.17 to 1.32), FV&N (1.05 to 1.19), and oils & fats (1.00 to 1.19). These consistently high elasticities signal an ongoing dietary transition driven by unmet consumption needs and aspirations for more diverse diets.

In contrast, more economically advanced regions —especially Europe and the Americas —exhibit a declining trend in income elasticities for most food groups, consistent with Engel's Law, saturation effects, and population aging. For example, Europe's elasticity for ASF falls from 0.69 in 2021 to 0.38 in 2050, while condiments & sweeteners drop from 0.73 to 0.59. Exceptions to this pattern are discretionary foods. Income elasticities for processed meals & snacks, FAFH, and beverages are projected to rise in all regions, highlighting a growing demand for convenience associated with higher real incomes and urban lifestyles.

[35] They are the same as highlighted in Figure 4 and Table C8.

		ASF	Beans	Condi-ments	F V & N	Grains	Processed meals	Oils & fats	FAFH	All bever-ages
Africa	2021	1.35	1.17	0.89	1.05	0.81	0.99	1.00	0.95	1.04
	2030	1.38	1.32	0.93	1.12	0.89	1.14	1.09	0.89	1.09
	2040	1.39	1.33	1.03	1.16	0.92	1.16	1.15	0.90	1.11
	2050	1.38	1.32	1.09	1.19	0.94	1.16	1.19	1.00	1.14
Americas	2021	0.84	1.06	0.80	0.82	0.59	0.94	0.92	0.42	0.70
	2030	0.74	1.10	0.74	0.83	0.63	1.03	0.92	0.75	0.75
	2040	0.64	1.07	0.69	0.81	0.64	1.03	0.89	1.10	0.78
	2050	0.53	1.01	0.63	0.78	0.64	1.02	0.85	1.48	0.80
Asia-Oc	2021	0.94	0.59	0.77	0.79	0.51	0.49	0.73	1.47	0.82
	2030	0.86	0.52	0.76	0.77	0.51	0.45	0.71	1.76	0.84
	2040	0.75	0.53	0.72	0.78	0.55	0.52	0.71	2.17	0.89
	2050	0.66	0.56	0.68	0.78	0.59	0.59	0.71	2.49	0.94
Europe	2021	0.69	0.87	0.73	0.86	0.69	0.88	0.86	1.97	0.94
	2030	0.59	0.87	0.71	0.87	0.72	0.92	0.87	2.32	0.98
	2040	0.49	0.86	0.66	0.85	0.74	0.95	0.85	2.69	1.02
	2050	0.38	0.84	0.59	0.84	0.76	0.97	0.82	3.04	1.05

Table 4. **Baseline and projected income elasticities, under scenario SSP2, by food group and region.** SSP: Shared Socioeconomic Pathways. SSP2: "Middle of the road" scenario. ASF: animal-sourced food, FAFH: food away from home, FV&N: fruits,vegetables & nuts. Oc: Oceania.

An exception to the general decline in income elasticities across non-discretionary food groups is grains & starchy staples, for which elasticities are projected to rise modestly in all regions. This counterintuitive pattern likely reflects compositional shifts within the category, as rising incomes are increasingly directed toward higher-value, processed, or convenience-oriented grain products rather than coarse or bulk staple consumption (Bellemare et al., 2024). In lower-income regions such as Africa, the increase may also capture persistent caloric shortfalls and continued reliance on staple-based diets as incomes grow. In higher-income regions, the upward trend may be driven by urbanization dynamics, with urban households relying more heavily on packaged breads, breakfast cereals, and ready-to-eat grain product forms, which tend to be more income-responsive than traditional staples (Harding and Lovenheim, 2017).

Global average projected elasticities results for the other SSP scenarios are presented in Table C14. The findings reveal variation across scenarios, driven by differences in projected sociodemographic trajectories. Notably, SSP3 yields the lowest projected income elasticities, reflecting its limited rise in urbanization —a factor strongly and positively associated with income elasticities, as shown in Table 3.

Table 5 presents the results of our global food demand projection exercise under SSP2. We compare results using constant predicted income elasticities estimated as of 2021 and time-varying projected elasticities estimated using population-weighted average projected sociodemographic characteristics. The projections based on constant income elasticities are lower than those based on time-varying projected elasticities, except for ASF and condiments & sweeteners. The gap between demand projections based on time-varying income elasticities and those based on constant elasticities widens over time, reflecting the growing influence of changing sociodemographic conditions on food demand. By 2050, the projections based on time-varying elasticities are higher by 1.6% for beans, lentils, peas & soy, 1.8% for FV&N, 5.7% for grains & starchy staples, and 1.9% for oils & fats. They are lower than the projections based on constant elasticities for ASF by 10.7% and for condiments & sweeteners by 1.9%.

Table C16 presents the projection results for each region under SSP2. As expected from the projected elasticity estimates in Table 4, projected demand based on time-varying elasticities is higher for all food groups in Africa under this scenario. However, it is similar to or lower than projections based on constant elasticities in other regions, except for grains & starchy staples. Table C17 presents the global projections for all other scenarios. Projected global ASF demand based on time-varying elasticities is lower for all SSP scenarios. The contrary is true for other food groups, except for SSP3 for which projected global demand based on time-varying elasticities is lower for all food groups.

	Baseline	Constant 2021 elasticities			Time-varying elasticities		
	2021	2030	2040	2050	2030	2040	2050
ASF	1259.0	1628.8	2087.8	2538.1	1608.1	1976.8	2265.9
Beans	76.3	94.6	116.9	137.8	94.5	117.3	140.0
Condiments	260.2	323.4	400.0	472.2	323.3	397.0	463.1
F V & N	1900.9	2390.5	2987.9	3558.0	2394.2	3012.5	3623.1
Grains	1962.3	2336.5	2782.0	3183.7	2347.7	2852.6	3364.2
Oils & fats	128.6	160.6	199.6	236.5	160.9	201.3	240.9

Table 5. **Projected global food consumption levels, under scenario SSP2, by food group, in million tons.** ASF: animal-sourced food, FV&N: fruits, vegetables & nuts. SSP: Shared Socioeconomic Pathways. SSP2: "Middle of the road" scenario.

5 Discussion

In line with the literature, we find that most data and model choices do not have a statistically significant effect on demand elasticity estimates (Bouyssou et al., 2024; Colen et al., 2018; Cornelsen et al., 2016). There are some notable exceptions for income elasticities. More flexible demand systems are associated with lower income elasticity estimates. As expected from economic theory and in line with Bouyssou et al. (2024)'s findings for ASF, income elasticities tend to be higher when estimated conditionally on food demand or on broader, more aggregated food categories. Using household income rather than total expenditure to measure income elasticities is associated with lower estimates, which is consistent with results found by Colen et al. (2018) in their meta-analysis in Africa. For price elasticities, compensated elasticities are associated with lower absolute values than uncompensated elasticities. This result aligns with theory for normal goods, since the (negative) income effect reinforces the substitution effect in the uncompensated elasticity.

Our findings provide empirical support for Engel's Law, particularly in more urbanized settings. Support for Bennett's Law is comparatively weaker. While discretionary foods like FAFH become more income-elastic as GDP per capita increases, real income growth has no statistically significant impact on ASF elasticities. Moreover, the responsiveness of grain & starchy staples demand to household income does not diminish more steeply with real income growth than it does for total food demand. A limitation of our analysis is the inability to examine substitution patterns within aggregated food groups — for example, between coarse and fine cereals or across quality tiers within a category. This reflects a common constraint in meta-analyses, where food group definitions vary across primary studies and must be harmonized to a common set of aggregated categories. As a result, our analysis may obscure within-group heterogeneity in income responsiveness. For example, recent micro-level evidence by Bellemare et al. (2024) in LMIC finds that as income rises, households substitute coarse staples with fine staples, and coarse staples with protein-rich foods, but not fine staples with protein-rich foods, suggesting a more nuanced hierarchy in food transitions than captured by broad staple or protein categories alone. Our aggregated grains & starchy staples grouping likely masks these distinctions.

To probe further, we re-estimate the meta-regression models separately for ASF, FV&N, and grains & starchy staples (Table C5, Table C6, and Table C7). Results confirm the negative association between GDP per capita and income elasticities, with statistical significance for rice. However, this classification does not clearly align with the fine and coarse staple distinctions in Bellemare et al. (2024), particularly given that this classification may be context-dependent. In the ASF category, we observe an overall statistically significant negative association with GDP per capita but a positive association for eggs and dairy. This is in line with Bouyssou et al. (2024)' findings. These same two categories show negative interactions with urbanization, which may reflect a transition from home production to market purchases. For FV&N, we find a divergence between fruits and vegetables as income elasticities for fruits and nuts increase with GDP per capita, whereas those for vegetables decline. This asymmetry may stem from differences in price sensitivity, perishability, and perceived necessity (Miller et al., 2016). As the literature almost exclusively aggregates these two subgroups, this result points to the need for future research with more granular food classifications to unpack these heterogeneous effects.

We find that urbanization is associated with higher income elasticity estimates but has no statistically significant effects on price elasticity estimates, consistent with findings from other meta-analyses (Bouyssou et al., 2024; Colen et al., 2018). Urbanization is a key factor influencing food consumption patterns. It is associated with reduced reliance on home-grown foods (Mendez and Popkin, 2004). Urban centers are more closely tied to world markets and, therefore, urban residents tend to have greater access to a diversity of food types and sources (Rosegrant et al., 2001). When exploring the interaction effect between real income growth and urbanization, we find that urbanization has a diminishing effect on the income elasticity of food demand as countries become wealthier. In LMIC settings, increases in urbanization are associated with a positive effect on income elasticities, likely reflecting improved access to markets, dietary diversification, and changing consumption preferences. The marginal impact of urbanization is smaller or negligible in HIC contexts, as diets are already diversified and further income gains exert limited influence on food demand patterns. We additionally explore the urbanization-income elasticities relationship by food group. We find that the positive association is more modest for ASF and beverages, likely explained by higher meat consumption and sugary drinks availability in urban settings (York and Gossard, 2004; Malik et al., 2013). The negative link between urbanization and FAFH income elasticities, and the weaker positive association for ASF and beverages, may reflect early adoption patterns and saturation effects in urban areas.

Population aging is associated with lower income elasticities, in line with the expectation that older individuals require fewer calories and exhibit more stable dietary preferences. To further probe this mechanism, we examined the role of youth and overall population dependency, finding no significant effects (Table D3). This suggests that the observed demographic effects on demand elasticities are primarily driven by aging rather than broader shifts in population structure.

Finally, we explored whether income inequality moderates the relationship between income and food demand by including the Gini index as an additional sociodemographic covariate. While the estimated interaction was not statistically significant, the coefficient was negative, suggesting that greater income inequality could possibly attenuate the responsiveness of demand to income. This direction aligns with the theoretical predictions of Cirera and Masset (2010), who argue that high income inequality between countries leads to a flattening of Engel curves when aggregating demand across heterogeneous populations, lowering the observed income elasticity at the macro level. In our case, the absence of a statistically significant effect may reflect limited variation in inequality across studies or measurement challenges in harmonizing Gini estimates across time and data sources. Nevertheless, our findings are consistent with the view that high inequality could possibly dampen the strength of aggregate income responses, even if not precisely estimated here.

Our predicted income elasticities are broadly consistent with those reported by Colen et al. (2018) in Africa, especially regarding relative magnitudes across food groups. As in their analysis, we find the highest income elasticity for ASF and the lowest for grains & starchy staples. However, our predicted elasticities for Africa are notably higher. This may stem from several methodological differences between the two studies. We estimate a larger and more up-to-date meta-sample. More importantly, we control for the conditionality of estimations (e.g., whether elasticities are conditional on food demand or broader expenditure) and explicitly model interactions with sociodemographic drivers. This feature allows us to more accurately capture heterogeneities in food demand responsiveness. We find that beverages exhibit the highest income elasticity in Africa —a pattern consistent with market analyses predicting rapid growth in carbonated soft drink consumption across the continent.[36] This is also in line with Colen et al. (2018)'s predicted elasticity results classifying beverages as income-elastic.

There is comparatively more existing literature on predicted price elasticities than income elasticities for specific food groups at the global level. One of the most widely cited works and the latest study available is Green et al. (2013), which synthesizes demand elasticities across food groups and income levels using studies published up to August 2011. Our analysis extends the evidence base by incorporating a broader set of more recent studies and accounting for important sources of heterogeneity such as urbanization and demographic characteristics.

Our results align well with Green et al. (2013)'s estimates for comparable food aggregates. Our predicted global elasticity for oils & fats is −0.51, which falls well within the range they report for low- to high-income countries (–0.42 to –0.60). The same is true for ASF (−0.69), FV&N (–0.67), and grains & starchy staples (–0.58), despite slight differences in group definitions.[37] Overall, we find that Asia-Oceania is the least price-sensitive region, in line with Bouyssou et al. (2024). In the absence of global estimates for FAFH price elasticity, our finding that FAFH is the most price-responsive food group is consistent with evidence from the U.S. (Andreyeva et al., 2010). Our global estimate for beverages (–0.76) also matches closely with the values reported by Andreyeva et al. (2010) for soft drinks and juice in the U.S. (–0.79 and –0.76, respectively). In regions like the Americas and Europe, where sugar-sweetened beverages (SSB) make up a large share of total beverage consumption, this aggregate likely reflects the high price-responsiveness of the beverages category (Andreyeva et al., 2022). Conversely, in Africa and Asia, where per capita SSB consumption is lower, this category may be dominated by water, tea, or other non-SSB, typically associated with lower price responsiveness (Muhammad et al., 2019).

We further predict income and price elasticities for disaggregated subgroups within ASF, FV&N, and grains & starchy staples, which represent the three Level 1 food groups with the largest sample sizes in our meta-sample (Figure 5).[38] Among ASF, pork has the lowest predicted income elasticity, while chicken & other poultry and dairy & whole milk products are the most income-elastic. Lower global income elasticities for pork and beef likely reflect cultural and religious dietary restrictions in highly populated regions such

[36] Grand View Research, Inc. Middle East & Africa Carbonated Soft Drink Market Size & Outlook, 2021 (Accessed 14 July 2025).

[37] Green et al. (2013) report the following ranges: meat, fish, and dairy (–0.6 to –0.8), fruit and vegetables (–0.53 to –0.72), and cereals: (–0.43 to –0.61).

[38] Table C11 shows the results in a table format.

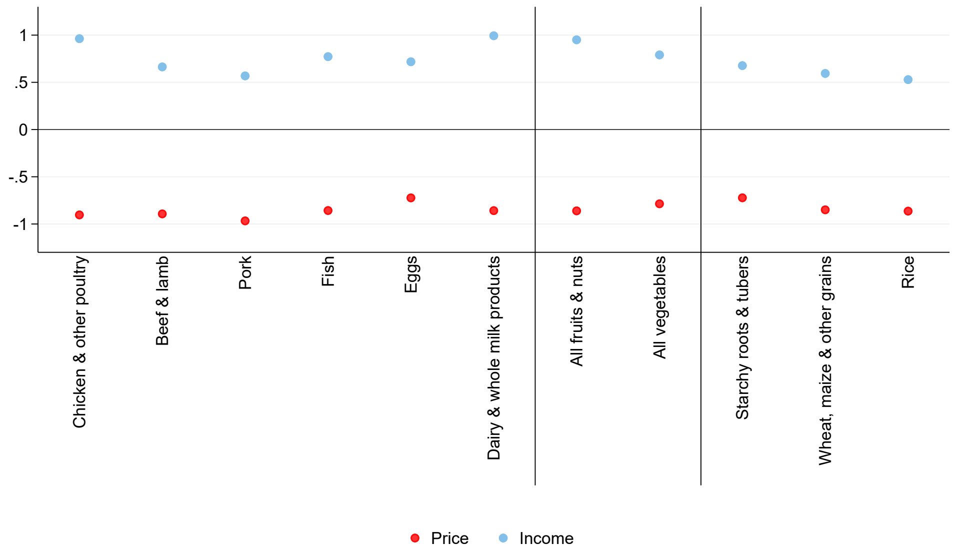

Figure 5. **Predicted income and price elasticities, by Level 3 food groups.** Based on the full sample. ASF: Animal source foods; FV&N: fruits, vegetables, and nuts. Results in table format can be found in Table C11. Standard errors are available upon request.

as Northern and Western Africa, the Middle East, and South Asia. Predicted income elasticities for grains & starchy staple subgroups are low and homogeneous, with values between 0.53 and 0.68, reflecting their status as dietary essentials in many parts of the world. In the FV&N category, predicted income and absolute price elasticities are notably higher for fruits & nuts than for vegetables, in line with McCullough et al. (2024)'s findings in Sub-Saharan Africa. Our predicted price elasticities for meat types (−0.86 to −0.97) fall within the range of Gallet (2010)'s predicted elasticity results for beef, pork, lamb, poultry, and fish (−0.78 to −1.17). Overall, disaggregation from Level 1 food groups reveals higher predicted price elasticity estimates, consistent with expectations that substitution possibilities are more pronounced at finer levels of food classification.

Others have previously attempted to project food demand accounting for changes in real income. In China, Zhou et al. (2020) investigate the relationship between income elasticities for meat and cereals and income growth through a meta-analysis, and then project such elasticities to 2030, accounting for changes in real per capita income. Yu et al. (2004) also argue that global food demand projections should rely on flexible demand systems that reflect declining income elasticities as consumers become wealthier. Building on these efforts, our study further incorporates changes in urbanization and population aging —two sociodemographic drivers that our meta-regression results identify as significant determinants of income elasticities.

Accounting for these dynamics and time-varying income elasticities leads to notable differences in projected global food demand. While the percentage differences with projections based on constant income elasticities might seem relatively small, they translate into large absolute quantity differences. By 2050, these differences are about −272.2 million tons for ASF, 2.2 million tons for beans, lentils, peas & soy, −9.1 million tons for condiments & sweeteners, 65.1 million tons for FV&N, 180.5 million tons for grains & starchy staples, and 4.4 million tons for oils & fats. For comparison, differences for ASF and grains & starchy staples represent approximately the total consumption in the Americas as of 2021 (Table C16). Zhou et al. (2020) also predict lower future income elasticities for meat, and consequently lower future demand, when accounting for time-varying elasticities in China. Their results for cereals are mixed, with higher projected future income elasticities for wheat but lower for other cereals.

Overall, the findings from this projection exercise underscore the importance of using time-varying income elasticities when projecting long-term consumption patterns, rather than assuming static preferences that may obscure structural dietary shifts. A limitation of our approach, and of related work such as Zhou et al. (2020), is the assumption of linear relationships between income elasticity estimates and sociodemographic drivers. While this assumption aids interpretation, it does not impose theoretical bounds on income elasticities, such as the expectation that they decline and eventually plateau as real income rises. Introducing non-linear interactions (e.g., quadratic terms) in the meta-regression would markedly increase the number of parameters, consuming degrees of freedom, and leaving too little scope to meaningfully assess between-study variability in our two-level random intercept model. For this reason, non-linear interactions with sociodemographic variables are not used in the literature (e.g., Bouyssou et al. (2024), Colen et al. (2018)).

Further limitations deserve consideration. By construction, meta-regression studies rely on sociodemographic variables that are often partially correlated. While we model their joint effects, this multicollinearity may reduce precision in projections and obscure underlying mechanisms. Although we account for an exhaustive list of methodological moderators in our main specification and sensitivity meta-regressions, information on the econometric method (e.g., seemingly unrelated regressions, maximum likelihood, least squares) was not explicitly reported in most primary studies. As a result, we could not systematically control for this factor, which may influence elasticity estimates (Gallet, 2010). Nevertheless, we do include demand model choice in our meta-regression model, which is correlated with the econometric method used. As in other global meta-regression analyses of food demand, our regional aggregates may mask within-region heterogeneity. For instance, Asia-Oceania-wide population-weighted average predicted estimates are influenced heavily by populous countries like China and India, and may not reflect trends in smaller economies.

6 Conclusions

This paper aimed to examine the extent to which empirical choices, such as data characteristics and estimation methods, account for the observed heterogeneity in food demand elasticities, assess whether theoretical predictions about the role of sociodemographic factors are supported by empirical evidence, and simulate how food demand is expected to vary with projected sociodemographic changes. It provides the most comprehensive global meta-analysis of food demand elasticities to date. We synthesized over four decades of peer-reviewed empirical evidence and collected more than 13,000 elasticity estimates covering 57 countries and five continents.

We find that while methodological and data choices generally have limited effects on demand estimates, income elasticities are more sensitive to model specification —particularly the choice of demand system model, conditional demand, and the choice of household income measure. Our large database additionally allowed us to add a set of sociodemographic variables and interactions in the meta-regressions characterizing the heterogeneity across world regions and products. Our findings indicate empirical support for Engel's Law, as food income elasticities decline with real income growth. This decline becomes more significant with urbanization. In contrast, support for Bennett's Law is mixed. While income elasticities increase with real income for some discretionary foods, they do not decline more steeply for staples than for total food demand, nor rise consistently for protein-rich foods like ASF. Importantly, we show that urbanization and population aging significantly shape income elasticities across food categories, suggesting that demand dynamics are not solely driven by income growth but also structural demographic shifts.

We generate predicted demand elasticities within a unified framework across four world regions and nine food groups, defined in line with global dietary guidelines. To our knowledge, this is the first study to produce meta-estimates of income elasticities for such a comprehensive set of food groups and regions, extending beyond prior efforts focused on specific items or geographies. We also update global meta-estimates of price elasticities, originally derived by Green et al. (2013), incorporating a decade of new evidence. Despite the wider scope and more recent data, our predicted elasticities remain broadly consistent with established findings.

Using sociodemographic projections from SSP scenarios, we show that income elasticities are not static: they tend to decline in higher-income regions for non-discretionary and essential food items, likely due to consumption saturation, while rising for most food groups in Africa. Assuming constant elasticities over time yields meaningfully different estimates of future food demand, particularly for ASF, underscoring the importance of incorporating sociodemographic dynamics into long-run demand models. These findings carry important implications for global food policy, market outlooks, and trade strategy. Our updated elasticity database, predicted elasticity estimates, and projections offer a valuable resource for researchers and policymakers to improve food demand modeling and inform policy design.

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Appendix

A. List of primary studies included in the meta-sample

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Back to Section 2.

B. Data appendix

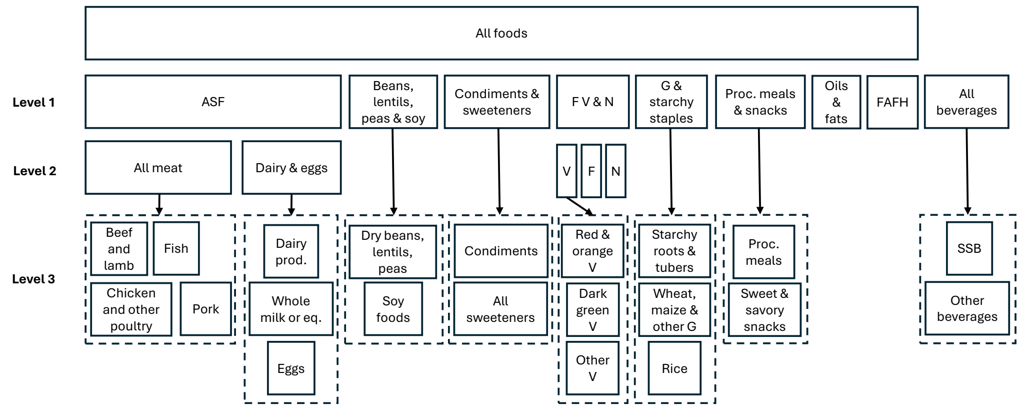

Figure B1. **Aggregation scheme of food categories.** ASF: animal-sourced foods; eq.: equivalent; FAFH: food away from home; FV&N: fruits, vegetables, and nuts; G: grains; Proc.: processed; prod.: products; SSB: sugar-sweetened beverages.
Back to Section 2.

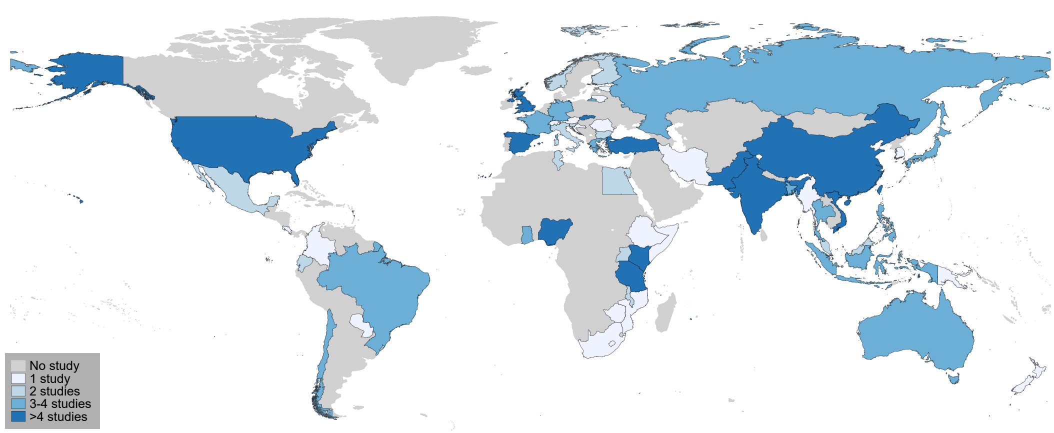

Figure B2. **Geographic distribution of studies in the meta-sample.** Based on the full sample, i.e., the 215 studies collected. The countries missing in the study are colored in light grey, and the intensity of blue indicates the number of studies by country. The scale represents quartiles.
Back to Section 2.

Variables included	Type	Description	Source	Included
Data variables				
Region	Cat.	Africa, Americas, Asia-Oceania, and Europe.	Authors	Y
Sample type	Cat.	Subsample and total.	Authors	Y
Data structure	Cat.	Cross-sectional & time series and panel data.	Authors	N
Data period	Cat.	Pre-2000, 2001-2010, and 2011-2020.	Authors	N
Data representativeness	Cat.	National and subnational.	Authors	N
Model variables				
Demand model type	Cat.	Single-equation and demand system.	Authors	Y
Demand system specification	Cat.	AIDS-, QUAIDS-, and other.	Authors	Y
Type of demand	Cat.	Conditional and unconditional.	Authors	Y
Type of income elasticity	Cat.	Total expenditure and income.	Authors	Y
Type of price elasticity	Cat.	Compensated and uncompensated.	Authors	Y
Censored demand	Cat.	Yes and no.	Authors	N
Number of estimation stages	Cat.	Single-stage and multi-stage.	Authors	N
Account for price endogeneity	Cat.	Yes and no.	Authors	N
Account for expenditure endogeneity	Cat.	Yes and no.	Authors	N
Control demographics	Cat.	Yes and no.	Authors	N
Sociodemographic				
Log(GDP pc)	Cont.	Logarithm of GDP per capita at country level in constant 2005 PPP international dollar.	WDI	Y
Urbanization	Cont.	Percentage of population in urban areas at country level.	WDI	Y
Population >64 yo	Cont	Population 65 yo or above.	WDI	Y
Population <15 yo	Cont	Population below 15 yo.	WDI	N
Population dependency ratio	Cont	Population below 15 yo and 65 yo or above over total population 15-64 yo.	WDI	N
Gini index	Cont.	Standardized Gini index.	UNU WIDER	N
Food groups				
Groups	Cat.	All foods, ASF, beans lentils peas & soy, condiments & sweeteners, FV&N, grains & starchy staples, processed meals & snacks, oils & fats, FAFH, and all beverages	Authors	Y

Table B1. **List of variables included in the meta-sample**. Authors: sourced from the meta-sample; Cont.: continuous; Cat.: Categorical; PPP: purchasing power parity; UNU WIDER: United Nations University World Institute for Development Economics Research; WDI: World Bank's World Development Indicators. Included: the variable is included in the main meta-regression specification. Y: yes; N: no. yo: years old.
Back to Section 3.1.

	Income elasticity			Price elasticity		
	Number	Mean	Sd	Number	Mean	Sd
ASF	**2,468**	**0.966**	**0.633**	**2,452**	**-0.899**	**0.752**
All meat	1,513	1.022	0.655	1,484	-0.924	0.806
Beef and lamb	209	0.918	0.663	252	-1.052	1.041
Chicken and other poultry	191	0.878	0.606	207	-0.901	0.865
Fish	169	0.813	0.532	173	-1.018	0.994
Pork	500	1.103	0.724	449	-0.868	0.736
Dairy & eggs	850	0.860	0.583	862	-0.873	0.679
Dairy products	390	0.896	0.673	406	-0.927	0.493
Whole milk or equivalents	186	0.979	0.540	216	-0.935	0.562
Eggs	184	0.714	0.479	162	-0.688	1.153
Beans lentils peas & soy	**166**	**0.824**	**0.686**	**171**	**-0.932**	**0.898**
Dry beans lentils & peas	99	0.905	0.786	111	-0.699	0.673
Soy foods	67	0.704	0.484	60	-1.363	1.090
Condiments & sweeteners	**263**	**0.615**	**0.759**	**293**	**-0.722**	**0.655**
Condiments	112	0.381	0.983	88	-0.891	0.851
All sweeteners	157	0.774	0.485	205	-0.650	0.536
F V & N	**1,247**	**0.835**	**0.491**	**1,191**	**-0.801**	**0.415**
All vegetables	518	0.761	0.426	502	-0.768	0.379
Dark green vegetables	11	0.842	0.522	8	-0.680	0.535
Red and orange vegetables	65	0.647	0.403	60	-0.799	0.197
Other vegetables	28	0.654	0.473	15	-1.057	0.360
All fruits	457	0.897	0.590	445	-0.803	0.385
Nuts	29	0.390	0.469	12	-0.666	0.321
Grains & starchy staples	**1,110**	**0.594**	**0.594**	**1,151**	**-0.804**	**0.740**
Rice	293	0.749	0.767	328	-0.867	0.706
Starchy roots and tubers	593	0.562	0.514	616	-0.804	0.794
Wheat, maize & other grains	174	0.406	0.510	157	-0.674	0.673
Processed meals & snacks	**204**	**0.608**	**0.775**	**309**	**-0.933**	**0.641**
Processed meals	88	0.670	0.623	116	-0.882	0.437
Sweet and savory snacks	116	0.561	0.873	193	-0.963	0.737
Oils & fats	**420**	**0.743**	**0.437**	**463**	**-0.626**	**0.508**
FAFH	**137**	**0.966**	**0.836**	**33**	**-1.130**	**0.669**
All beverages	**468**	**0.798**	**0.488**	**566**	**-1.081**	**0.625**
SSB	102	0.711	0.525	202	-1.114	0.729
Other beverages	109	0.612	0.448	151	-1.001	0.444

Table B2. **Descriptive statistics of elasticity estimates.** Bold are main food groups (Level 1). ASF: animal source foods; FAFH: food away from home; FV&N: fruits, vegetables, and nuts; SSB: sugar-sweetened beverages. Sd: standard deviation.

Back to Section 2.

	Income elasticity	Price elasticity
Test-statistic	-0.712	1.661
SE	0.117	0.188
Z	-6.076	8.830
p-value	0.000	0.000

Table B3. **Funnel-plot asymmetry test for publication bias.** Egger test. H_0: No publication bias. Back to Section 3.1.

	Income elasticity	Price elasticity
Log of sample size	-0.168***	-0.110***
	(0.020)	(0.020)
N	3172	4021
pseudo R^2	0.018	0.007

Table B4. **Correlation between significance level and logarithm of sample size.** Based on the fraction of the sample with significance level information. Ordered logit regression. Significance level equal to 1 if $p < 0.01$, 2 if $p < 0.05$, 3 if $p < 0.1$, and 4 if $p \geq 0.1$. Bootstrapped standard errors with 350 repetitions. Back to Section 3.1.

	Income elasticity			
	Africa	Americas	Asia-Oceania	Europe
Africa	-	-	-	
Americas	0.000	-	-	-
Asia-Oceania	0.651	0.000	-	-
Europe	0.486	0.000	0.831	-
	Price elasticity			
	Africa	Americas	Asia-Oceania	Europe
Africa	-	-	-	
Americas	0.776	-	-	-
Asia-Oceania	0.000	0.004	-	-
Europe	0.244	0.276	0.023	-

Table B5. **P-values matrices of t-test statistics for equality of elasticity estimates, by type and region.** Confidence level is set to 95%.

Back to Section 3.1.

C. Additional results

	Income elasticity	Price elasticity
Food groups		
ASF	-0.308	-2.043
	(0.780)	(2.043)
Beans, lentils, peas & soy	1.700	1.744
	(2.028)	(3.058)
Condiments & sweeteners	-2.559	-2.168
	(1.752)	(2.226)
F V & N	-0.546	-0.778
	(0.632)	(1.675)
Grains & starchy staples	-0.122	-1.316
	(0.956)	(1.818)
Processed meals & snacks	1.500	1.196
	(1.057)	(2.264)
Oils & fats	-0.753	-1.435
	(0.541)	(1.899)
FAFH	-0.766	-2.399***
	(0.890)	(0.885)
All beverages	-0.126	-1.452
	(0.962)	(2.068)
Data variables		
Subsample	0.001	0.064
	(0.019)	(0.056)
Model variables		
Demand system	-0.054	0.196
	(0.079)	(0.134)
Demand system × QUAIDS	-0.100***	0.008
	(0.020)	(0.010)
Demand system × Other	0.016	-0.106
	(0.033)	(0.097)
Conditional	0.249***	0.024
	(0.049)	(0.048)
Exp. measure: Income	-0.197**	
	(0.092)	
Compensated demand		0.111***
		(0.032)
Sociodemographic variables		
log(GDP pc)	-0.120**	0.212
	(0.056)	(0.421)
ASF × log(GDP pc)	0.128	0.309
	(0.113)	(0.311)
Beans × log(GDP pc)	-0.310	-0.074
	(0.273)	(0.421)
Condiments × log(GDP pc)	0.359	0.387
	(0.248)	(0.338)
F V & N × log(GDP pc)	0.090	0.120
	(0.097)	(0.254)
Grains × log(GDP pc)	-0.015	0.201
	(0.148)	(0.282)
Processed meals × log(GDP pc)	-0.303**	-0.134
	(0.138)	(0.335)
Oils & fats × log(GDP pc)	0.081	0.263
	(0.088)	(0.284)

FAFH × log(GDP pc)	0.338***	0.159
	(0.116)	(0.171)
All beverages × log(GDP pc)	0.062	0.206
	(0.147)	(0.308)
Urbanization	2.300***	-0.118
	(0.369)	(1.552)
ASF × Urbanization	-1.150***	-1.656
	(0.383)	(1.028)
Beans × Urbanization	1.543**	-4.310***
	(0.673)	(1.628)
Condiments × Urbanization	-1.313*	-2.144*
	(0.733)	(1.111)
F V & N × Urbanization	-0.838*	-0.855
	(0.428)	(0.902)
Grains × Urbanization	-0.566	-1.107
	(0.517)	(0.996)
Processed meals × Urbanization	1.345	-0.121
	(1.450)	(1.115)
Oils & fats × Urbanization	-0.258	-1.862**
	(0.570)	(0.909)
FAFH × Urbanization	-6.207***	1.992
	(0.896)	(1.390)
All beverages × Urbanization	-1.462**	-1.202
	(0.663)	(1.121)
Pop >64 yo	-4.399***	-4.005
	(1.452)	(6.267)
ASF × Pop >64 yo	0.085	0.258
	(1.367)	(3.300)
Beans × Pop >64 yo	3.085	13.932**
	(2.859)	(5.953)
Condiments × Pop >64 yo	0.464	-1.430
	(2.625)	(3.699)
F V & N × Pop >64 yo	2.952***	0.611
	(1.030)	(2.914)
Grains × Pop >64 yo	4.309*	0.923
	(2.279)	(3.352)
Processed meals × Pop >64 yo	4.549***	1.174
	(1.725)	(3.277)
Oils & fats × Pop >64 yo	2.252*	1.388
	(1.237)	(3.078)
FAFH × Pop >64 yo	17.713***	-6.397
	(5.522)	(12.471)
All beverages × Pop >64 yo	5.107***	0.607
	(1.415)	(3.776)
Regions		
Africa	0.355**	0.215
	(0.146)	(0.384)
Americas	-0.247**	-0.055
	(0.097)	(0.487)
Asia-Oceania	0.104	0.414
	(0.089)	(0.496)
Publication bias correction term	-0.772	0.629
	(0.708)	(1.489)
Constant	0.935**	-2.611
	(0.462)	(2.396)
N	6572	6701
Number of studies	186	199
Number of countries	54	55

Conditional R^2	0.454	0.553
Variance of error terms	0.268	0.302
Variance of random effects	0.119	0.280

Table C1. **Meta-regression estimates, displaying all coefficients**. Reference categories are underlined in Table B1.

Back to Section 4.1.

	(1)	(2)	(3)	(4)	(5)	(6)
Data variables						
Subsample		-0.002	-0.003	-0.002	0.001	0.001
		(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Model variables						
Demand system		-0.025	-0.015	-0.101	-0.067	-0.054
		(0.052)	(0.078)	(0.070)	(0.083)	(0.079)
Demand system × QUAIDS		-0.085***	-0.074**	-0.082***	-0.086***	-0.100***
		(0.026)	(0.034)	(0.029)	(0.027)	(0.020)
Demand system × Other		-0.007	-0.031	-0.015	-0.010	0.016
		(0.035)	(0.047)	(0.041)	(0.040)	(0.033)
Conditional		0.214***	0.215***	0.228***	0.249***	0.249***
		(0.050)	(0.054)	(0.050)	(0.049)	(0.049)
Exp. measure: Income		-0.229***	-0.226**	-0.216**	-0.198**	-0.197**
		(0.089)	(0.090)	(0.090)	(0.092)	(0.092)
Sociodemographic variables						
log(GDP pc)			0.071	-0.168***	-0.095	-0.120**
			(0.067)	(0.064)	(0.063)	(0.056)
Urbanization				1.535***	2.069***	2.300***
				(0.272)	(0.278)	(0.369)
Pop >64 yo					-5.120***	-4.399***
					(1.679)	(1.452)
Regions						
Africa						0.355**
						(0.146)
Americas						-0.247**
						(0.097)
Asia-Oceania						0.104
						(0.089)
Publication bias correction term	-0.844	-0.736	-0.720	-0.770	-0.747	-0.772
	(0.656)	(0.669)	(0.667)	(0.703)	(0.692)	(0.708)
Constant	0.842***	0.823***	0.157	1.468***	0.952**	0.935**
	(0.061)	(0.062)	(0.569)	(0.498)	(0.479)	(0.462)
N	6572	6572	6572	6572	6572	6572
Number of studies	186	186	186	186	186	186
Number of countries	54	54	54	54	54	54
Conditional R^2	0.324	0.383	0.458	0.477	0.496	0.454
Variance of error terms	0.282	0.279	0.273	0.271	0.268	0.268
Variance of random effects	0.108	0.108	0.125	0.129	0.137	0.119
Food groups	Yes	Yes	Yes	Yes	Yes	Yes
Food groups × SDV	No	No	Yes	Yes	Yes	Yes

Table C2. **Meta-regression estimates for income elasticities, step-by-step introduction**. Reference categories are underlined in Table B1. The main specification results are presented in Table 3 and Table C1. SDV: socio-demographic variables.
Back to Section 4.1.

	(1)	(2)	(3)	(4)	(5)	(6)
Data variables						
Subsample		0.062	0.063	0.063	0.063	0.064
		(0.055)	(0.055)	(0.055)	(0.056)	(0.056)
Model variables						
Demand system		0.446***	0.356***	0.225*	0.206	0.196
		(0.113)	(0.127)	(0.127)	(0.136)	(0.134)
Demand system × QUAIDS		0.009	0.009	0.009	0.009	0.008
		(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Demand system × Other		-0.179**	-0.178**	-0.111	-0.106	-0.106
		(0.085)	(0.074)	(0.085)	(0.095)	(0.097)
Conditional		0.007	0.016	0.018	0.024	0.024
		(0.045)	(0.046)	(0.049)	(0.048)	(0.048)
Compensated demand		0.106***	0.109***	0.110***	0.111***	0.111***
		(0.031)	(0.031)	(0.032)	(0.032)	(0.032)
Sociodemographic variables						
log(GDP pc)			0.050	0.278	0.321	0.212
			(0.183)	(0.293)	(0.315)	(0.421)
Urbanization				-1.950**	-1.073	-0.118
				(0.894)	(0.713)	(1.552)
Pop >64 yo					-6.781**	-4.005
					(3.389)	(6.267)
Regions						
Africa						0.215
						(0.384)
Americas						-0.055
						(0.487)
Asia-Oceania						0.414
						(0.496)
Publication bias correction term	1.035	0.462	0.457	0.673	0.855	0.629
	(0.991)	(1.215)	(1.228)	(1.415)	(1.556)	(1.489)
Constant	-0.849***	-0.997***	-1.341	-2.397	-2.677	-2.611
	(0.120)	(0.080)	(1.796)	(2.339)	(2.465)	(2.396)
N	6701	6701	6701	6701	6701	6701
Number of studies	199	199	199	199	199	199
Number of countries	55	55	55	55	55	55
Conditional R^2	0.397	0.456	0.465	0.553	0.580	0.553
Variance of error terms	0.312	0.311	0.308	0.304	0.302	0.302
Variance of random effects	0.198	0.240	0.233	0.271	0.298	0.280
Food groups	Yes	Yes	Yes	Yes	Yes	Yes
Food groups × SDV	No	No	Yes	Yes	Yes	Yes

Table C3. **Meta-regression estimates for price elasticities, step-by-step introduction**. Reference categories are underlined in Table B1. The main specification results are presented in Table 3 and Table C1. SDV: socio-demographic variables.
Back to Section 4.1.

	Income elasticity			Price elasticity		
	Full	LMIC	HIC	Full	LMIC	HIC
Data variables						
Subsample	0.001	0.006	-0.025	0.064	0.021	0.126
	(0.019)	(0.022)	(0.044)	(0.056)	(0.023)	(0.146)
Model variables						
Demand system	-0.054	-0.158*	0.429	0.196	-0.177	-0.368
	(0.079)	(0.094)	(0.342)	(0.134)	(0.136)	(0.315)
Demand system × QUAIDS	-0.100***	-0.021	-0.085**	0.008	0.379***	0.001***
	(0.020)	(0.064)	(0.041)	(0.010)	(0.033)	(0.000)
Demand system × Other	0.016	0.058	0.048**	-0.106	-0.139	-0.001
	(0.033)	(0.106)	(0.022)	(0.097)	(0.108)	(0.028)
Conditional	0.249***	0.247***	0.236	0.024	-0.013	0.973
	(0.049)	(0.050)	(0.200)	(0.048)	(0.019)	(0.638)
Exp. measure: Income	-0.197**	-0.200**	0.753***			
	(0.092)	(0.091)	(0.225)			
Compensated demand				0.111***	0.080***	0.246
				(0.032)	(0.019)	(0.151)
Sociodemographic variables						
log(GDP pc)	-0.120**	-0.127**	-0.554	0.212	0.259	-1.597**
	(0.056)	(0.065)	(1.009)	(0.421)	(0.276)	(0.653)
Urbanization	2.300***	2.336***	5.016**	-0.118	-0.801	-5.454***
	(0.369)	(0.256)	(2.061)	(1.552)	(0.582)	(1.802)
Pop >64 yo	-4.399***	-6.067***	-1.308	-4.005	-7.143**	1.237
	(1.452)	(1.745)	(8.074)	(6.267)	(3.573)	(6.395)
Regions						
Africa	0.355**			0.215		
	(0.146)			(0.384)		
Americas	-0.247**			-0.055		
	(0.097)			(0.487)		
Asia-Oceania	0.104			0.414		
	(0.089)			(0.496)		
Publication bias correction term	-0.772	-0.988	-0.327***	0.629	3.093***	-2.576
	(0.708)	(1.224)	(0.126)	(1.489)	(1.124)	(2.537)
Constant	0.935**	1.293***	2.400	-2.611	-2.170	19.677***
	(0.462)	(0.477)	(10.692)	(2.396)	(2.042)	(6.920)
N	6572	4800	1772	6701	4560	2141
Number of studies	186	116	72	199	118	82
Number of countries	54	41	13	55	41	14
Conditional R^2	0.454	0.428	0.873	0.553	0.550	0.775
Variance of error terms	0.268	0.336	0.110	0.302	0.334	0.249
Variance of random effects	0.119	0.119	0.378	0.280	0.249	0.486
Food groups × SDV	Yes	Yes	Yes	Yes	Yes	Yes

Table C4. **MRA estimates, by country income group**. Reference categories are underlined in Table B1. Column (1) and Column (4) refer to the main specification results presented in Table 3 and Table C1. Country income group categorization by the World Bank as of 1987. HIC: high-income countries, LMIC: low- and middle-income countries. SDV: socio-demographic variables.
Back to Section 4.1.

	Income elasticity		Price elasticity	
	(1)	(2)	(3)	(4)
Food groups				
Beef & lamb	-0.322	4.583	0.026	4.863
	(0.506)	(2.893)	(0.311)	(3.477)
Pork	-0.395	-1.549	-0.029	-0.987
	(0.381)	(2.031)	(0.244)	(2.638)
Fish	-0.213	-1.561	0.104	4.213
	(0.260)	(2.653)	(0.218)	(3.648)
Eggs	-0.152	-2.022*	0.281	-0.829
	(0.106)	(1.062)	(0.390)	(5.258)
Dairy & whole milk	0.012	-2.717**	0.135	2.578
	(0.214)	(1.348)	(0.221)	(3.121)
Data variables				
Subsample	-0.042	-0.043	0.141	0.142
	(0.035)	(0.035)	(0.148)	(0.148)
Model variables				
Demand system	0.021	0.181	0.141	0.208
	(0.129)	(0.147)	(0.387)	(0.372)
Demand system × QUAIDS	0.236**	0.124	0.006***	0.006***
	(0.096)	(0.106)	(0.002)	(0.002)
Demand system × Other	-0.011	-0.003	-0.017	-0.015
	(0.041)	(0.037)	(0.068)	(0.066)
Conditional	0.208**	0.210**	0.121	0.122
	(0.099)	(0.100)	(0.139)	(0.139)
Exp. measure: Income	-0.076	-0.074		
	(0.156)	(0.157)		
Compensated demand			0.164**	0.164**
			(0.077)	(0.077)
Sociodemographic variables				
log(GDP pc)	-0.188***	-0.143	1.970*	2.186***
	(0.051)	(0.328)	(1.025)	(0.785)
Beef & lamb × log(GDP pc)		-1.022*		-0.572
		(0.583)		(0.590)
Pork × log(GDP pc)		0.024		0.307
		(0.411)		(0.447)
Fish × log(GDP pc)		0.192		-0.518
		(0.473)		(0.553)
Eggs × log(GDP pc)		0.317**		0.391
		(0.157)		(0.937)
Dairy × log(GDP pc)		0.465**		-0.289
		(0.236)		(0.495)
Urbanization	0.889***	0.186	-6.401**	-5.693***
	(0.180)	(1.994)	(2.826)	(2.047)
Beef & lamb × Urbanization		7.304*		-0.171
		(3.765)		(3.130)
Pork × Urbanization		0.942		-2.972
		(2.654)		(2.247)
Fish × Urbanization		-2.285		0.909
		(3.008)		(2.025)
Eggs × Urbanization		-2.273**		-4.707
		(0.924)		(4.763)
Dairy × Urbanization		-2.548**		-0.472
		(1.237)		(1.948)
Pop >64 yo	-0.164	-3.440	-7.362	-9.370
	(1.031)	(3.455)	(7.700)	(8.421)
Beef & lamb × Pop >64 yo		3.761		5.024

		(4.072)		(5.609)
Pork × Pop >64 yo		4.197		-2.265
		(3.842)		(4.470)
Fish × Pop >64 yo		9.397*		0.721
		(5.080)		(6.206)
Eggs × Pop >64 yo		1.661		0.838
		(2.737)		(7.218)
Dairy × Pop >64 yo		-0.813		4.003
		(3.502)		(4.911)
Publication bias correction term	0.766	1.047	1.297	1.254
	(0.836)	(0.886)	(2.780)	(2.764)
Constant	2.045***	2.186	-15.089*	-17.265**
	(0.452)	(1.671)	(8.077)	(6.719)
N	1829	1829	1865	1865
Number of studies	162	162	168	168
Number of countries	52	52	54	54
Conditional R^2	0.316	0.474	0.780	0.786
Variance of error terms	0.431	0.373	0.553	0.530
Variance of random effects	0.151	0.185	1.162	1.118

Table C5. **Meta-regression estimates for ASF**. Reference categories are underlined in Table B1. The reference food group category is all chicken & other poultry. ASF: Animal sourced food.
Back to Section 5.

	Income elasticity		Price elasticity	
	(1)	(2)	(3)	(4)
Food groups				
All vegetables	-0.161***	1.839**	0.091	-1.792
	(0.056)	(0.929)	(0.097)	(1.098)
Data variables				
Subsample	-0.038	-0.038	-0.052*	-0.052*
	(0.027)	(0.027)	(0.030)	(0.030)
Model variables				
Demand system	0.086	0.056	-0.459**	-0.439**
	(0.230)	(0.229)	(0.217)	(0.212)
Demand system × QUAIDS	0.251	0.260	0.004***	0.004***
	(0.166)	(0.163)	(0.000)	(0.000)
Demand system × Other	-0.263	-0.236	0.374**	0.347**
	(0.193)	(0.191)	(0.185)	(0.177)
Conditional	0.279***	0.268***	-0.018*	-0.014
	(0.085)	(0.089)	(0.009)	(0.012)
Exp. measure: Income	-0.329***	-0.337***		
	(0.113)	(0.115)		
Compensated demand			0.060***	0.060***
			(0.017)	(0.017)
Sociodemographic variables				
log(GDP pc)	0.104	0.229*	0.057	-0.039
	(0.118)	(0.137)	(0.232)	(0.217)
All vegetables × log(GDP pc)		-0.325**		0.270*
		(0.137)		(0.163)
Urbanization	2.581***	2.065***	-1.232	-0.912
	(0.416)	(0.471)	(1.148)	(1.170)
All vegetables × Urbanization		1.200**		-0.868
		(0.505)		(0.572)
Pop >64 yo	-8.199**	-9.649***	-5.500	-5.128
	(3.310)	(3.336)	(3.761)	(3.693)
All vegetables × Pop >64 yo		3.159**		-1.181
		(1.599)		(1.398)
Publication bias correction term	0.561	0.531	2.947	2.994
	(1.827)	(1.830)	(1.968)	(1.976)
Constant	-0.847	-1.553	0.117	0.780
	(1.039)	(1.168)	(1.750)	(1.586)
N	1004	1004	959	959
Number of studies	119	119	119	119
Number of countries	47	47	48	48
Conditional R^2	0.842	0.840	0.871	0.872
Variance of error terms	0.109	0.105	0.070	0.067
Variance of random effects	0.355	0.335	0.264	0.256

Table C6. **Meta-regression estimates for F V & N**. Reference categories are underlined in Table B1. The reference food group category for columns (2) and (4) is all fruits & nuts. FV&N: fruits, vegetables, and nuts.

Back to Section 5.

	Income elasticity		Price elasticity	
	(1)	(2)	(3)	(4)
Food groups				
Wheat, maize & other grains	0.003	-0.041	-0.223	-2.416
	(0.132)	(0.688)	(0.160)	(2.103)
Rice	-0.118	1.744**	0.131	-8.412**
	(0.137)	(0.759)	(0.221)	(3.393)
Data variables				
Subsample	0.037	0.038	0.071*	0.086*
	(0.027)	(0.027)	(0.042)	(0.046)
Model variables				
Demand system	0.201	0.249*	-0.261	-0.301
	(0.130)	(0.149)	(0.298)	(0.312)
Demand system × QUAIDS	-0.102***	-0.104***	0.009***	0.009***
	(0.038)	(0.037)	(0.001)	(0.001)
Demand system × Other	-0.103	-0.109	-0.016	-0.042
	(0.140)	(0.166)	(0.115)	(0.132)
Conditional	0.150***	0.150***	-0.012	-0.013
	(0.034)	(0.034)	(0.014)	(0.014)
Exp. measure: Income	-0.161***	-0.161***		
	(0.051)	(0.051)		
Compensated demand			0.090***	0.096***
			(0.018)	(0.020)
Sociodemographic variables				
log(GDP pc)	-0.222	-0.275	-0.300	-0.591*
	(0.171)	(0.183)	(0.186)	(0.338)
Grains × log(GDP pc)		0.117		0.363
		(0.105)		(0.317)
Rice × log(GDP pc)		-0.233*		1.410**
		(0.131)		(0.553)
Urbanization	-0.719	0.057	4.569***	5.721***
	(1.230)	(1.741)	(0.961)	(1.518)
Grains × Urbanization		-2.596***		-1.514
		(0.680)		(2.395)
Rice × Urbanization		0.272		-7.169*
		(0.987)		(3.896)
Pop >64 yo	3.187*	1.938	-12.627**	-11.172
	(1.879)	(2.396)	(5.578)	(7.241)
Grains × Pop >64 yo		3.667*		-1.948
		(2.174)		(7.279)
Rice × Pop >64 yo		0.890		-6.280
		(4.618)		(18.196)
Publication bias correction term	-2.234	-2.357	0.544	0.477
	(1.786)	(1.831)	(1.542)	(1.507)
Constant	2.694**	2.875***	0.893	2.751
	(1.057)	(1.048)	(1.335)	(2.384)
N	1060	1060	1100	1100
Number of studies	132	132	135	135
Number of countries	47	47	49	49
Conditional R^2	0.783	0.870	0.781	0.781
Variance of error terms	0.093	0.085	0.198	0.189
Variance of random effects	0.233	0.375	0.513	0.485

Table C7. **Meta-regression estimates for grains & starchy staples**. Reference categories are underlined in Table B1. The reference food group category for columns (2) and (4) is starchy roots & tubers.
Back to Section 5.

	Africa		Americas		Asia-Oc		Europe		**Global**	
	I	P	I	P	I	P	I	P	**I**	**P**
ASF	1.35	-0.93	0.84	-1.16	0.94	-0.44	0.69	-1.17	**0.98**	**-0.69**
Beans	1.17	-0.90	1.06	-1.73	0.59	-0.26	0.87	-0.61	**0.78**	**-0.60**
Condiments	0.89	-0.71	0.80	-1.10	0.77	-0.26	0.73	-1.20	**0.79**	**-0.54**
F V & N	1.05	-0.80	0.82	-1.07	0.79	-0.46	0.86	-1.14	**0.84**	**-0.67**
Grains	0.81	-0.80	0.59	-0.97	0.51	-0.36	0.69	-0.99	**0.59**	**-0.58**
Processed meals	0.99	-0.51	0.94	-0.95	0.49	-0.40	0.88	-1.08	**0.68**	**-0.55**
Oils & fats	1.00	-0.74	0.92	-1.04	0.73	-0.25	0.86	-0.96	**0.81**	**-0.51**
FAFH	0.95	-1.10	0.42	-0.80	1.47	-0.92	1.97	-1.59	**1.29**	**-1.00**
All beverages	1.04	-0.95	0.70	-1.18	0.82	-0.53	0.94	-1.21	**0.86**	**-0.76**

Table C8. **Predicted income and price elasticities, by region and food group.** Oc: Oceania. ASF: Animal source foods; FAFH: Food away from home; Veg.: Vegetables. I: Income; P: Price. Standard errors can be found in Table C10.
Back to Section 4.2.

	Africa		Americas		Asia-Oc		Europe		**Global**	
	U	C	U	C	U	C	U	C	**U**	**C**
ASF	-0.96	-0.85	-1.18	-1.07	-0.47	-0.36	-1.20	-1.09	**-0.72**	**-0.61**
Beans	-0.92	-0.81	-1.76	-1.64	-0.29	-0.18	-0.63	-0.52	**-0.62**	**-0.51**
Condiments	-0.73	-0.62	-1.13	-1.02	-0.28	-0.17	-1.22	-1.11	**-0.56**	**-0.45**
F V & N	-0.83	-0.72	-1.09	-0.98	-0.49	-0.38	-1.17	-1.06	**-0.69**	**-0.58**
Grains	-0.82	-0.71	-1.00	-0.89	-0.38	-0.27	-1.02	-0.90	**-0.60**	**-0.49**
Processed meals	-0.53	-0.42	-0.98	-0.87	-0.42	-0.31	-1.10	-0.99	**-0.58**	**-0.47**
Oils & fats	-0.77	-0.65	-1.06	-0.95	-0.28	-0.17	-0.99	-0.87	**-0.54**	**-0.42**
FAFH	-1.12	-1.01	-0.83	-0.71	-0.94	-0.83	-1.61	-1.50	**-1.02**	**-0.91**
All beverages	-0.97	-0.86	-1.20	-1.09	-0.56	-0.45	-1.24	-1.13	**-0.78**	**-0.67**

Table C9. **Predicted uncompensated and compensated price elasticities, by region and food group.** Oc: Oceania. ASF: Animal source foods; FAFH: Food away from home; Veg.: Vegetables. C: compensated; U: uncompensated. Standard errors are available upon request.
Back to Section 4.2.

	Africa		Americas		Asia-Oc		Europe		**Global**	
	I	P	I	P	I	P	I	P	**I**	**P**
ASF	0.64	0.78	0.63	0.85	0.63	0.77	0.63	0.78	**0.63**	**0.77**
Beans	0.65	0.81	0.63	0.85	0.63	0.78	0.64	0.81	**0.63**	**0.78**
Condiments	0.63	0.78	0.63	0.85	0.63	0.77	0.64	0.79	**0.63**	**0.77**
F V & N	0.63	0.77	0.63	0.85	0.63	0.77	0.63	0.78	**0.62**	**0.77**
Grains	0.63	0.77	0.63	0.85	0.63	0.77	0.64	0.78	**0.63**	**0.77**
Processed meals	0.73	0.79	0.64	0.85	0.70	0.78	0.63	0.78	**0.67**	**0.78**
Oils & fats	0.63	0.78	0.63	0.85	0.63	0.77	0.64	0.78	**0.63**	**0.77**
FAFH	0.70	0.96	0.63	0.82	0.63	0.78	0.75	1.18	**0.63**	**0.77**
All beverages	0.64	0.79	0.63	0.85	0.63	0.77	0.64	0.79	**0.63**	**0.78**

Table C10. **Standard errors for predicted income and price elasticities, by region and food group.** Oc: Oceania. ASF: Animal source foods; FAFH: Food away from home; Veg.: Vegetables. I: Income; P: Price. Estimates can be found in Table C8.
Back to Section 4.2.

	Income	Price
ASF		
Chicken & other poultry	0.96	-0.90
Beef & lamb	0.66	-0.89
Pork	0.57	-0.97
Fish	0.77	-0.86
Eggs	0.72	-0.72
Dairy & whole milk products	0.99	-0.86
F V & N		
All fruits & nuts	0.95	-0.86
All vegetables	0.79	-0.79
Grains & starchy staples		
Starchy roots & tubers	0.68	-0.72
Wheat, maize & other grains	0.59	-0.85
Rice	0.53	-0.86

Table C11. **Predicted global income and price elasticities, for Level 3 ASF, FV&N, and grains & starchy staples.** ASF: Animal source foods; FV&N: fruits, vegetables, and nuts. Standard errors are available upon request.
Back to Section 5.

		2021	2050				
			SSP1	SSP2	SSP3	SSP4	SSP5
Africa	GDP per capita	4,089	11,940	8,051	4,821	5,050	15,308
	Urbanization	0.44	0.71	0.58	0.54	0.70	0.71
	Population >64 yo	0.03	0.10	0.07	0.05	0.06	0.10
	Population (total, millions)	1,401	1,765	2,014	2,338	2,256	1,738
Americas	GDP per capita	27,269	45,240	39,800	31,176	39,445	54,223
	Urbanization	0.82	0.92	0.90	0.54	0.91	0.92
	Population >64 yo	0.12	0.25	0.21	0.18	0.22	0.24
	Population (total, millions)	1,019	1,139	1,196	1,231	1,134	1,190
Asia-Oc	GDP per capita	12,521	31,737	24,748	18,053	21,726	38,988
	Urbanization	0.51	0.74	0.62	0.54	0.74	0.74
	Population >64 yo	0.09	0.23	0.19	0.15	0.20	0.23
	Population (total, millions)	4,721	4,790	5,197	5,707	5,021	4,786
Europe	GDP per capita	27,571	53,503	49,860	39,136	50,950	61,302
	Urbanization	0.75	0.90	0.85	0.54	0.87	0.90
	Population >64 yo	0.19	0.33	0.29	0.28	0.31	0.30
	Population (total, millions)	743	770	762	681	716	848
Global	**GDP per capita**	**14,308**	**31,405**	**25,133**	**18,011**	**22,099**	**38,507**
	Urbanization	**0.56**	**0.77**	**0.67**	**0.54**	**0.76**	**0.78**
	Population >64 yo	**0.10**	**0.21**	**0.17**	**0.14**	**0.17**	**0.21**
	Population (total, millions)	**7,885**	**8,463**	**9,169**	**9,956**	**9,127**	**8,561**

Table C12. **Population-weighted average of sociodemographic variables in 2021 and SSP projections for 2050, by scenario and region.** SSP: Shared Socioeconomic Pathways. SSP1: Sustainability ("taking the green road"); SSP2: "Middle of the road"; SSP3: Regional rivalry ("a rocky road"); SSP4: Inequality ("a road divided"); and SSP5: Fossil-fueled development ("taking the highway"). GDP per capita in 2005 constant purchasing power parity international dollars. Oc: Oceania.
Back to Section 4.3.

		2021	2030	2040	2050
Africa	GDP per capita	4,089	4,458	5,969	8,051
	Urbanization	0.44	0.50	0.54	0.58
	Population >64 yo	0.03	0.04	0.05	0.07
	Population (total, millions)	1,401	1,523	1,777	2,014
Americas	GDP per capita	27,269	29,809	34,531	39,800
	Urbanization	0.82	0.86	0.88	0.90
	Population >64 yo	0.12	0.15	0.18	0.21
	Population (total, millions)	1,019	1,099	1,157	1,196
Asia-Oc	GDP per capita	12,521	16,353	20,716	24,748
	Urbanization	0.51	0.53	0.58	0.62
	Population >64 yo	0.09	0.12	0.16	0.19
	Population (total, millions)	4,721	4,888	5,096	5,197
Europe	GDP per capita	27,571	35,943	43,063	49,860
	Urbanization	0.75	0.80	0.83	0.85
	Population >64 yo	0.19	0.23	0.26	0.29
	Population (total, millions)	743	756	760	762
Global	**GDP per capita**	**14,308**	**17,747**	**21,488**	**25,133**
	Urbanization	**0.56**	**0.60**	**0.63**	**0.67**
	Population >64 yo	**0.10**	**0.12**	**0.15**	**0.17**
	Population (total, millions)	**7,885**	**8,266**	**8,790**	**9,169**

Table C13. **Population-weighted average of sociodemographic variables in 2021 and SSP2 projections, by region.** SSP: Shared Socioeconomic Pathways. SSP2: "Middle of the road" scenario. GDP per capita in 2005 constant purchasing power parity international dollars. Oc: Oceania.

Back to Section 4.3.

		ASF	Beans	Condi-ments	F V & N	Grains	Processed meals	Oils & fats	FAFH	All bever-ages
Baseline	2021	0.98	0.78	0.79	0.84	0.59	0.68	0.81	1.29	0.86
	2030	0.94	0.94	0.84	0.92	0.70	0.86	0.91	1.44	0.94
	2040	0.84	0.98	0.82	0.95	0.76	0.96	0.95	1.83	1.00
SSP1	2050	0.72	1.01	0.77	0.96	0.82	1.04	0.95	2.27	1.07
	2030	0.92	0.77	0.79	0.85	0.61	0.70	0.82	1.52	0.89
	2040	0.84	0.79	0.77	0.86	0.65	0.75	0.83	1.81	0.93
SSP2	2050	0.78	0.81	0.75	0.88	0.69	0.80	0.85	2.08	0.97
	2030	0.88	0.60	0.72	0.77	0.52	0.52	0.71	1.63	0.84
	2040	0.81	0.57	0.68	0.76	0.53	0.52	0.69	1.89	0.86
SSP3	2050	0.78	0.57	0.66	0.76	0.54	0.54	0.69	2.04	0.88
	2030	0.98	1.02	0.82	0.94	0.72	0.93	0.94	1.29	0.94
	2040	0.93	1.17	0.80	0.99	0.81	1.11	1.00	1.48	1.01
SSP4	2050	0.89	1.31	0.78	1.03	0.90	1.28	1.06	1.64	1.08
	2030	0.95	0.91	0.86	0.92	0.69	0.83	0.92	1.44	0.93
	2040	0.85	0.92	0.86	0.94	0.74	0.90	0.95	1.83	0.99
SSP5	2050	0.73	0.93	0.83	0.95	0.79	0.96	0.95	2.28	1.05

Table C14. **Global baseline and projected income elasticities, by food group and scenario.** SSP: Shared Socioeconomic Pathways. SSP1: Sustainability ("taking the green road"); SSP2: "Middle of the road"; SSP3: Regional rivalry ("a rocky road"); SSP4: Inequality ("a road divided"); and SSP5: Fossil-fueled development ("taking the highway").

Back to Section 4.3.

FAO code	FAO name	This study's grouping
2848	Milk	ASF
2733	Pork	ASF
2734	Poultry	ASF
2731	Beef	ASF
2744	Eggs	ASF
2761	Freshwater fish	ASF
2732	Mutton & goat	ASF
2764, 2762, 2763	Marine fish	ASF
2768, 2736, 2735	Other meat	ASF
2769, 2767, 2766, 2765	Other seafood	ASF
2547	Peas	Beans, lentils, peas & soy
2555	Soyabeans	Beans, lentils, peas & soy
2546	Beans	Beans, lentils, peas & soy
2549, 2557, 2561	Other pulses & seeds	Beans, lentils, peas & soy
2536	Sugar cane	Condiments & sweeteners
2542	Sugar products	Condiments & sweeteners
2640	Pepper	Condiments & sweeteners
2641, 2642, 2645	Other spices	Condiments & sweeteners
2543, 2745, 2536, 2541, 2537	Other sweeteners	Condiments & sweeteners
2619	Dates	F V & N
2560	Coconuts	F V & N
2620	Grapes	F V & N
2611	Oranges & mandarins	F V & N
2617	Apples	F V & N
2615	Bananas	F V & N
2612, 2613, 2614, 2618, 2625, 2563	Other fruits	F V & N
2601	Tomatoes	F V & N
2602	Onions	F V & N
2605, 2775	Other vegetables	F V & N
2551	Nuts	F V & N
2556, 2552	Groundnuts	F V & N
2511	Wheat	Grains & starchy staples
2805, 2807	Rice	Grains & starchy staples
2514	Maize	Grains & starchy staples
2532	Cassava	Grains & starchy staples
2531	Potatoes	Grains & starchy staples
2518	Sorghum	Grains & starchy staples
2517	Millet	Grains & starchy staples
2533	Sweet potatoes	Grains & starchy staples
2616	Plantains	Grains & starchy staples
2516, 2515, 2513, 2520	Other cereals	Grains & starchy staples
2535, 2534	Other roots	Grains & starchy staples
2571	Soybean oil	Oils & fats
2577	Palm oil	Oils & fats
2573	Sunflower oil	Oils & fats
2740	Butter and ghee	Oils & fats
2574	Rape and mustard oil	Oils & fats
2737	Raw animal fats	Oils & fats
2572	Groundnut oil	Oils & fats
2580	Olive oil	Oils & fats
2575	Cottonseed oil	Oils & fats
2578	Coconut oil	Oils & fats

2782, 2781, 2579, 2581, 2576, 2582, 2586, 2562, 2558, 2559, 2743, 2570	Other oils & oilcrops	Oils & fats

Table C15. **FAO Food Balances commodity regrouping**. ASF: animal-sourced foods, FV&N: fruits, vegetables, and nuts. FAO: Food and Agriculture Organization of the United Nations.
Back to Section 3.3.

	Baseline	Constant 2021 elasticities			Time-varying elasticities		
	2021	2030	2040	2050	2030	2040	2050
Africa							
ASF	92.3	112.7	195.2	331.5	112.9	198.3	338.2
Beans	17.8	21.5	35.2	56.6	21.7	37.4	62.7
Condiments	35.7	41.9	63.3	93.5	42.0	66.8	107.6
F V & N	170.7	203.2	322.3	500.5	204.3	335.7	548.7
Grains	447.2	521.2	769.8	1111.0	524.8	802.6	1215.5
Oils & fats	15.0	17.7	27.7	42.5	17.9	29.3	48.2
Americas							
ASF	290.4	337.4	401.8	468.0	334.4	383.3	416.0
Beans	8.3	9.9	12.1	14.6	9.9	12.2	14.4
Condiments	55.4	64.1	75.9	88.0	63.8	74.0	82.4
F V & N	217.5	252.3	299.7	348.3	252.4	298.9	343.4
Grains	200.2	227.4	261.0	293.3	228.4	264.4	299.8
Oils & fats	28.0	32.8	39.5	46.5	32.8	39.2	45.4
Asia-Oc							
ASF	642.1	854.8	1113.1	1341.9	837.6	1010.7	1104.8
Beans	47.6	57.8	69.2	78.4	56.6	67.2	76.9
Condiments	133.9	170.2	212.9	249.0	170.0	207.3	233.7
F V & N	1329.6	1698.3	2132.1	2500.5	1692.3	2121.6	2496.0
Grains	1158.2	1375.0	1617.8	1807.1	1372.9	1648.6	1907.7
Oils & fats	63.6	80.0	99.0	114.9	79.5	98.0	113.8
Europe							
ASF	234.2	285.6	325.0	360.3	278.6	297.2	300.5
Beans	2.5	3.2	3.7	4.2	3.2	3.7	4.2
Condiments	35.3	43.6	50.0	55.8	43.4	48.4	51.4
F V & N	183.1	233.7	274.4	312.0	234.3	274.0	308.6
Grains	156.7	191.1	217.6	241.3	193.0	223.1	252.0
Oils & fats	22.1	28.2	33.1	37.6	28.2	32.9	36.8

Table C16. **Projected food demand, by food group and region, under scenario SSP2, in million tons.** ASF: animal-sourced food, FV&N: fruits, vegetables & nuts. SSP: Shared Socioeconomic Pathways. SSP2: Middle of the road. Oc: Oceania.
Back to Section 4.3.

	Baseline	Constant 2021 elasticities			Time-varying elasticities		
	2021	2030	2040	2050	2030	2040	2050
SSP1							
ASF	1259.0	1710.2	2317.9	2912.0	1692.6	2147.4	2377.1
Beans	76.3	97.8	125.7	151.4	102.4	140.8	181.5
Condiments	260.2	334.3	430.8	519.7	339.0	438.3	511.6
F V & N	1900.9	2482.7	3246.8	3964.1	2538.5	3438.5	4323.6
Grains	1962.3	2375.9	2900.8	3352.0	2452.5	3196.4	4001.8
Oils & fats	128.6	166.4	215.8	261.7	171.5	232.7	292.0
SSP2							
ASF	1259.0	1628.8	2087.8	2538.1	1608.1	1976.8	2265.9
Beans	76.3	94.6	116.9	137.8	94.5	117.3	140.0
Condiments	260.2	323.4	400.0	472.2	323.3	397.0	463.1
F V & N	1900.9	2390.5	2987.9	3558.0	2394.2	3012.5	3623.1
Grains	1962.3	2336.5	2782.0	3183.7	2347.7	2852.6	3364.2
Oils & fats	128.6	160.6	199.6	236.5	160.9	201.3	240.9
SSP3							
ASF	1259.0	1490.1	1771.9	1990.5	1476.4	1718.7	1901.1
Beans	76.3	88.6	103.5	115.3	87.1	99.6	109.9
Condiments	260.2	302.6	353.7	394.1	300.7	346.9	382.7
F V & N	1900.9	2221.9	2610.5	2915.6	2207.1	2571.4	2861.2
Grains	1962.3	2239.2	2570.6	2839.0	2224.6	2541.6	2807.9
Oils & fats	128.6	149.9	175.6	195.8	148.4	171.7	190.2
SSP4							
ASF	1259.0	1561.7	1928.8	2228.1	1562.6	1900.9	2149.3
Beans	76.3	91.4	109.6	124.1	95.4	124.6	156.2
Condiments	260.2	312.4	374.8	424.6	314.0	376.4	423.5
F V & N	1900.9	2303.9	2788.0	3176.9	2340.8	2921.0	3446.1
Grains	1962.3	2274.4	2646.3	2937.0	2327.2	2849.4	3360.2
Oils & fats	128.6	155.0	186.7	212.0	158.4	198.5	235.8
SSP5							
ASF	1259.0	1833.0	2674.2	3594.6	1812.2	2443.6	2817.2
Beans	76.3	103.4	141.2	179.7	108.3	156.0	207.3
Condiments	260.2	353.9	484.2	617.5	362.6	510.0	644.6
F V & N	1900.9	2637.3	3677.7	4763.6	2710.0	3945.8	5302.0
Grains	1962.3	2481.3	3171.6	3825.0	2571.8	3531.1	4648.3
Oils & fats	128.6	176.4	243.4	312.5	183.1	267.2	358.5

Table C17. **Projected global food demand, by food group and scenario, in million tons.** ASF: animal-sourced food, FV&N: fruits, vegetables & nuts. SSP: Shared Socioeconomic Pathways. SSP1: Sustainability ("taking the green road"); SSP2: "Middle of the road"; SSP3: Regional rivalry ("a rocky road"); SSP4: Inequality ("a road divided"); and SSP5: Fossil-fueled development ("taking the highway").
Back to Section 4.3.

D. Robustness

	Income elasticity			Price elasticity		
	(1)	(2)	(3)	(4)	(5)	(6)
Data variables						
Subsample	0.001	0.001	-0.000	0.064	0.064	0.062
	(0.019)	(0.019)	(0.019)	(0.056)	(0.056)	(0.056)
Data period						
2001-2010			-0.063			-0.343
			(0.042)			(0.239)
2011-2020			-0.097			0.020
			(0.069)			(0.336)
Panel		-0.062			0.059	
		(0.063)			(0.096)	
Subnational		-0.044			0.096	
		(0.070)			(0.162)	
Model variables						
Demand system	-0.054	-0.051	-0.058	0.196	0.199	0.206
	(0.079)	(0.078)	(0.079)	(0.134)	(0.134)	(0.145)
Demand system × QUAIDS	-0.100***	-0.104***	-0.093***	0.008	0.009	0.008
	(0.020)	(0.018)	(0.024)	(0.010)	(0.010)	(0.010)
Demand system × Other	0.016	0.016	0.008	-0.106	-0.107	-0.131
	(0.033)	(0.033)	(0.036)	(0.097)	(0.097)	(0.096)
Conditional	0.249***	0.249***	0.250***	0.024	0.024	0.024
	(0.049)	(0.049)	(0.049)	(0.048)	(0.048)	(0.049)
Exp. measure: Income	-0.197**	-0.197**	-0.197**			
	(0.092)	(0.092)	(0.092)			
Compensated demand				0.111***	0.111***	0.111***
				(0.032)	(0.032)	(0.032)
Censored demand		0.042			-0.036	
		(0.027)			(0.108)	
Multi-stage		-0.047			-0.170	
		(0.075)			(0.136)	
Acc. expenditure endog.		0.144			-0.216	
		(0.113)			(0.136)	
Acc. price endog.		-0.149			0.105	
		(0.107)			(0.152)	
Control for demographics		0.012			-0.272	
		(0.084)			(0.188)	
Sociodemographic variables						
log(GDP pc)	-0.120**	-0.121**	-0.017	0.212	0.210	0.326
	(0.056)	(0.056)	(0.099)	(0.421)	(0.421)	(0.279)
Urbanization	2.300***	2.305***	1.978***	-0.118	-0.110	-1.481
	(0.369)	(0.372)	(0.357)	(1.552)	(1.560)	(1.727)
Pop >64 yo	-4.399***	-4.381***	-4.182***	-4.005	-3.957	2.530
	(1.452)	(1.455)	(1.369)	(6.267)	(6.267)	(5.209)
Regions						
Africa	0.355**	0.353**	0.441***	0.215	0.199	0.424
	(0.146)	(0.150)	(0.166)	(0.384)	(0.410)	(0.477)
Americas	-0.247**	-0.251***	-0.311***	-0.055	-0.091	0.077
	(0.097)	(0.095)	(0.116)	(0.487)	(0.477)	(0.270)
Asia-Oceania	0.104	0.105	0.095	0.414	0.420	0.401
	(0.089)	(0.090)	(0.085)	(0.496)	(0.498)	(0.461)
Publication bias correction term	-0.772	-0.766	-0.768	0.629	0.568	0.562
	(0.708)	(0.726)	(0.704)	(1.489)	(1.525)	(1.379)

Constant	0.935**	0.949**	0.218	-2.611	-2.373	-3.368**
	(0.462)	(0.464)	(0.768)	(2.396)	(2.514)	(1.455)
N	6572	6572	6572	6701	6701	6701
Number of studies	186	186	186	199	199	199
Number of countries	54	54	54	55	55	55
Conditional R^2	0.454	0.459	0.467	0.553	0.546	0.568
Variance of error terms	0.268	0.268	0.268	0.302	0.302	0.300
Variance of random effects	0.119	0.118	0.125	0.280	0.253	0.269
Food groups	Yes	Yes	Yes	Yes	Yes	Yes
Food groups × SDV	Yes	Yes	Yes	Yes	Yes	Yes

Table D1. **Robustness: Meta-regression estimates including additional variables**. Reference categories are underlined in Table 1. Columns (1) and (4) represent the main specification, i.e., same as columns (1) and (2) of Table 3. Columns (2) and (5) include additional data and model variables. Columns (3) and (6) include the data period.
Back to Section 4.1.

	Income elasticity			Price elasticity			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Data variables							
Subsample	0.001	-0.003	0.041	0.064	0.066	0.075	0.050
	(0.019)	(0.019)	(0.037)	(0.056)	(0.053)	(0.055)	(0.058)
Model variables							
Demand system	-0.054	-0.059	-0.010	0.196	0.197	0.139	0.073
	(0.079)	(0.081)	(0.078)	(0.134)	(0.134)	(0.122)	(0.117)
Demand system × QUAIDS	-0.100***	-0.094***	-0.135***	0.008	0.008	0.004	0.008
	(0.020)	(0.020)	(0.035)	(0.010)	(0.010)	(0.004)	(0.010)
Demand system × Other	0.016	0.014	0.022	-0.106	-0.105	-0.126	-0.121
	(0.033)	(0.033)	(0.030)	(0.097)	(0.097)	(0.089)	(0.079)
Conditional	0.249***	0.250***	0.264***	0.024	0.024	-0.018	0.016
	(0.049)	(0.049)	(0.041)	(0.048)	(0.048)	(0.019)	(0.046)
Exp. measure: Income	-0.197**	-0.197**	-0.230***				
	(0.092)	(0.092)	(0.069)				
Compensated demand				0.111***	0.111***	0.100***	0.104***
				(0.032)	(0.032)	(0.021)	(0.016)
Sociodemographic variables							
log(GDP pc)	-0.120**	-0.109*	-0.067	0.212	0.203	0.053	0.070
	(0.056)	(0.060)	(0.067)	(0.421)	(0.414)	(0.248)	(0.201)
Urbanization	2.300***	2.244***	2.355***	-0.118	-0.068	0.723	0.099
	(0.369)	(0.332)	(0.392)	(1.552)	(1.531)	(1.163)	(1.011)
Pop >64 yo	-4.399***	-4.714***	-5.262***	-4.005	-3.711	-1.489	-0.810
	(1.452)	(1.619)	(1.512)	(6.267)	(6.193)	(4.472)	(3.645)
Regions							
Africa	0.355**	0.328***	0.383***	0.215	0.250	0.522	0.412
	(0.146)	(0.124)	(0.148)	(0.384)	(0.404)	(0.368)	(0.300)
Americas	-0.247**	-0.259**	-0.274***	-0.055	-0.038	0.187	0.054
	(0.097)	(0.105)	(0.092)	(0.487)	(0.473)	(0.243)	(0.183)
Asia-Oceania	0.104	0.077	0.115	0.414	0.442	0.721**	0.550**
	(0.089)	(0.068)	(0.084)	(0.496)	(0.492)	(0.343)	(0.253)
Publication bias correction term	-0.772		-0.941	0.629		0.880	0.614
	(0.708)		(0.763)	(1.489)		(1.222)	(1.292)
Constant	0.935**	0.871*	0.459	-2.611	-2.576	-1.954	-1.721
	(0.462)	(0.480)	(0.533)	(2.396)	(2.357)	(1.387)	(1.110)
N	6572	6572	6517	6701	6701	6588	6511
Number of studies	186	186	186	199	199	198	199
Number of countries	54	54	54	55	55	55	55
Conditional R^2	0.454	0.446	0.534	0.553	0.561	0.651	0.622
Variance of error terms	0.268	0.268	0.196	0.302	0.302	0.140	0.202
Variance of random effects	0.119	0.114	0.109	0.280	0.292	0.177	0.255
Food groups	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Food groups × SDV	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table D2. **Robustness: Meta-regression estimates under various methods**. Reference categories are underlined in Table 1. Columns (1) and (4) represent the main specification, i.e., same as columns (1) and (2) of Table 3. Columns (2) and (5) remove the publication bias correction term. Columns (3) and (6) exclude outliers outside the range $[Q1 - 3 \times IQR, Q3 + 3 \times IQR]$. Column (7) excludes non-negative price elasticities.

Back to Section 4.1.

	Income elasticity					Price elasticity			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Data variables									
Subsample	0.001	0.001	-0.002	0.002	0.001	0.064	0.064	0.065	0.065
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.056)	(0.056)	(0.055)	(0.056)
Model variables									
Demand system	-0.054	-0.029	-0.059	-0.063	-0.042	0.196	0.241	0.251	0.167
	(0.079)	(0.075)	(0.069)	(0.075)	(0.079)	(0.134)	(0.147)	(0.166)	(0.119)
Demand system × QUAIDS	-0.100***	-0.100***	-0.098***	-0.104***	-0.108***	0.008	0.008	0.008	0.009
	(0.020)	(0.020)	(0.020)	(0.020)	(0.018)	(0.010)	(0.010)	(0.010)	(0.010)
Demand system × Other	0.016	0.009	0.004	0.020	0.021	-0.106	-0.096	-0.085	-0.057
	(0.033)	(0.033)	(0.035)	(0.032)	(0.033)	(0.097)	(0.092)	(0.093)	(0.105)
Conditional	0.249***	0.248***	0.227***	0.248***	0.249***	0.024	0.023	0.025	0.028
	(0.049)	(0.049)	(0.050)	(0.049)	(0.049)	(0.048)	(0.048)	(0.048)	(0.049)
Exp. measure: Income	-0.197**	-0.196**	-0.216**	-0.196**	-0.197**				
	(0.092)	(0.092)	(0.089)	(0.092)	(0.092)				
Compensated demand						0.111***	0.111***	0.109***	0.110***
						(0.032)	(0.032)	(0.032)	(0.031)
Sociodemographic variables									
log(GDP pc)	-0.120**	-0.194**	-0.294***	-0.177**	0.041	0.212	0.209	0.210	0.542
	(0.056)	(0.077)	(0.089)	(0.082)	(0.115)	(0.421)	(0.367)	(0.363)	(0.423)
Urbanization	2.300***	2.465***	2.518***	2.620***	5.757***	-0.118	-0.204	-0.214	-0.296
	(0.369)	(0.578)	(0.538)	(0.390)	(1.389)	(1.552)	(1.448)	(1.701)	(1.449)
Pop >64 yo	-4.399***	-6.020**		-4.298***	-3.057***	-4.005	-2.841		-9.273
	(1.452)	(2.497)		(1.595)	(0.966)	(6.267)	(7.497)		(7.197)
Pop <15 yo		-1.049					0.348		
		(0.764)					(1.480)		
Pop. dependence			-0.274					0.323	
			(0.282)					(0.665)	
Gini				-0.357					-1.598
				(0.251)					(0.978)
log(GDP pc) × Urbanization					-0.438**				
					(0.184)				
Regions									
Africa	0.355**	0.356**	0.588***	0.411**	0.230	0.215	0.261	0.490*	0.172
	(0.146)	(0.158)	(0.187)	(0.167)	(0.194)	(0.384)	(0.372)	(0.285)	(0.346)
Americas	-0.247**	-0.206**	-0.089	-0.198*	-0.073	-0.055	-0.034	0.080	-0.274
	(0.097)	(0.098)	(0.087)	(0.103)	(0.098)	(0.487)	(0.469)	(0.307)	(0.449)
Asia-Oceania	0.104	0.107	0.280**	0.163*	-0.021	0.414	0.404	0.591**	0.313
	(0.089)	(0.093)	(0.134)	(0.092)	(0.150)	(0.496)	(0.503)	(0.252)	(0.478)
Publication bias correction term	-0.772	-0.691	-0.742	-0.804	-0.792	0.629	0.653	0.450	0.442

	(0.708)	(0.713)	(0.739)	(0.727)	(0.711)	(1.489)	(1.510)	(1.332)	(1.467)
Constant	0.935**	1.900***	2.024***	1.386**	-0.222	-2.611	-2.715	-3.214	-4.334**
	(0.462)	(0.715)	(0.754)	(0.616)	(0.735)	(2.396)	(1.975)	(2.623)	(2.012)
N	6572	6572	6572	6572	6572	6701	6701	6701	6701
Number of studies	186	186	186	186	186	199	199	199	199
Number of countries	54	54	54	54	54	55	55	55	55
Conditional R^2	0.454	0.464	0.470	0.457	0.436	0.553	0.558	0.544	0.601
Variance of error terms	0.268	0.265	0.267	0.266	0.268	0.302	0.302	0.303	0.300
Variance of random effects	0.119	0.120	0.126	0.122	0.109	0.280	0.280	0.276	0.323
Food groups	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Food groups × SDV	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table D3. **Robustness: Meta-regression estimates including additional sociodemographic variables**. Reference categories are underlined in Table 1. Columns (1) and (6) represent the main specification, i.e., same as columns (1) and (2) of Table 3. Columns (2) and (7) include population below 15 years old. Columns (3) and (8) include population dependency. Columns (4) and (9) include gini (source: The World Income Inequality Database - WIID, Companion dataset, 2025). Column (5) include an interaction term between GDP per capita and urbanization.

Back to Section 4.1.

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