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Income elasticities for food, calories and nutrients across Africa: A meta-analysis

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ABSTRACT

This paper aims to provide a better understanding of the relationship between income and the demand for different types of food, nutrients, and calories in Africa by conducting a meta-analysis of income elasticity estimates. We build a meta-sample consisting of 1523 food-income elasticities, 369 nutrient-income elasticities, and 123 calorie-income elasticities extracted from 66 primary studies covering 48 African countries. The sample displays a large heterogeneity in income elasticity estimates, which our meta-analysis aims to explain by looking into attributes of the primary studies and characteristics of the countries considered. There are significant differences in the size of the income elasticities across food and nutrient groups. Foods that make up basic diets tend to have lower income elasticities, while elasticities are considerably higher for less basic and more aspirational foods. The role of methodological attributes of the primary studies in explaining heterogeneity is found to be small. Overall, our results confirm that although income growth in Africa will increase food consumption and lead to more nutritionally diverse diets, it is also associated with excessive intakes of fats and sugars, raising concerns about over-, in addition to undernutrition. This suggests that income-based policies can still play a role in the fight against hunger, but that targeted programs are needed to promote nutritionally valuable and healthy diets.

1. Introduction

Official estimations indicate that over 200 million people in Africa are hungry (FAO, IFAD & WFP, 2015). The share of undernourished people in SSA has declined substantially over the past decades (from 27.6% in 1990–1992 to 20.7% in 2010–2012), but at a considerably slower pace than in the rest of the developing world (World Bank, 2016). Given that the population of Sub-Saharan Africa (SSA) is expected to double by 2050 (UNPD, 2015), feeding the poor will remain an enormous challenge. Not only will the demand for food continue to rise, also the composition of food demand will change with rising incomes. Demand for food may shift towards more expensive, but not necessarily more nutritional food items as incomes increase (Behrman and Deolalikar, 1987), and also growing urbanisation will contribute to changes in the nutritional composition of diets with not only undernutrition, but also overnutrition becoming a concern (Popkin, 1994).

By and large, the existing literature on income and food demand has focused on the relationship between income and calorie consumption (i.e. calorie-income elasticities), while relatively few studies have considered the diet or nutrient composition (e.g. fats, proteins, carbohydrates) (Salois et al., 2012). The distinction is important because many African countries face specific nutrient deficiencies (e.g. proteins, vitamins), despite normal, or close to normal, levels of calorie intake. Moreover, concerns arise in the context of the 'nutrition transition', the shift in caloric intake towards fat-rich and sugar-rich diets as incomes grow. Haddad et al. (2003) have estimated in how far income growth can reduce underweight among children. Yet, deeper insights are needed on how income growth relates to the composition of diets in terms of nutrients and type of goods, in order to understand how to fight problems of under- but also overnutrition. In this paper we therefore study in detail the income elasticity of intake of different types of food, calorific intake and nutrient intake for Africa.

Generally, food demand is income inelastic (elasticities are less than one), reflecting Engel's law that food budget shares decline when

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income rises.[1] Studies have shown that the relationship between income and calorie consumption is not linear and that the increase in the demand for calories as a result of income growth becomes smaller as income levels become higher (i.e. income elasticities are not constant). This is thought to result from the reaching of a saturation point in calorie consumption (e.g. Skoufias et al., 2011; Salois et al., 2012). Studies have also found evidence that increased income leads to a preference for higher quality foods and more diversified diets, which may result in fewer calories (per unit of cost) than basic staple food diets (e.g. Skoufias et al., 2011) while delivering better nutrition. Evidence for developed countries (and increasingly also for developing countries), however, suggests that, overall, rising country income levels can lead to calorie overconsumption (leading to obesity), while the nutritional value of diets does not necessarily improve. In some developing countries, especially in their largest cities, the two realities of undernutrition and overnutrition often coexist, reflecting the "nutrition paradox" (Caballero, 2005). However, as Fabiosa (2011) notes, underlying these general trends, countries at similar stages of economic development have very different dietary patterns. This might be due to a variety of different factors including food supply structures, degree of urbanisation and, more generally, different cultures and food consumption habits. It follows that projections on future food demand, and the effectiveness of income-based policy mechanisms in addressing food and nutrition security may vary across regions including across Africa.

In this paper we examine the relation between income and food, calorie and nutrient demand in Africa through a systematic review of the existing literature. We carry out a meta-analysis to explain the large heterogeneity in income elasticities across the African continent The paper draws on several recent review studies, including other meta-analyses of food demand (e.g. Bouis and Haddad, 1992, Salois et al., 2012, Ogundari and Abdulai, 2013, Zhou and Yu, 2014), which are summarized in Table A.1 in Appendix. Our study builds on previous studies in three ways. First, most review studies focused on the relation between income and calorie consumption. This study provides evidence for income elasticities associated with different types of food and nutrients, besides calories, in order to improve our understanding of the relationship between income, diet composition and nutrition. The exception is the study by Salois et al. (2012) which considered different nutrient-income elasticities (including carbohydrates, proteins and fats), yet based on a smaller sample and without controlling for methodological attributes which may influence the results. Second, we consider a comprehensive list of potential sources of variation in income elasticities, relating to the attributes of the primary studies as well as the countries they refer to. Previous reviews and meta-analyses have mostly focused either on the data and methodological attributes of the primary studies (Bouis and Haddad, 1992; Ogundari and Abdulai, 2013), or on country income levels (Zhou and Yu, 2014; Salois et al. 2012), but not on both at the same time. Chen et al. (2015) do control for both sources of variation simultaneously, but focus on China only. Moreover, we also include urbanisation rates and geographical controls, which were not considered in previous studies. Thirdly, none of the previous meta-analyses provides specific evidence for Africa. Teklu (1996) does provide a qualitative review of food demand studies for Sub-Saharan Africa, and also Bouis and Haddad (1992) include a few African studies in their overview. Yet, given the large number of new studies estimating the food-income relation in Africa since then, an update of the literature and a systematic approach are appropriate. As such, this study provides the first meta-analysis of income elasticities of food demand for Africa.

The remainder of the paper is organised as follows. Section 2 provides a summary of the meta-sample construction and research methods used. Section 3 presents the key descriptive statistics of the meta-sample, the results from the meta-regression models and sensitivity tests, while Section 4 discusses the key implications from our findings, and section 5 concludes.

2. Data and research methods

2.1. Selection of primary studies and construction of the meta-sample

To identify the candidate primary studies to be included in the meta-sample, a search was carried out using a combination of terms including: "nutrition and income elasticity", "food and income elasticity", "calorie-income elasticity" and the combination of "income elasticity" and "demand elasticity" with a list of keywords such as "developing countries", "Africa", "food", "calorie", "nutrition", type of food (e.g. "eggs", "dairy", "milk", "cereal", "fruit", "vegetable", "fish", "meat").[2] The search was carried out across various online databases including both published peer-reviewed literature (e.g. journal articles) and 'grey' literature (e.g. working papers, reports) in the economics, medical and nutrition disciplines. Database searches were performed between October 2014 and February 2015. The databases searched were: ISI Web of Knowledge, ScienceDirect, EconLit, PubMed, AJOL (African Journals Online), World Bank, AgEcon, USAID (US Agency for International Development), FAO (UN Food and Agriculture Organisation), IFPRI (International Food Policy Research Institute), RePEc (Research Papers in Economics), and Google Scholar. In addition, we also considered the references of primary studies included in previous review studies of food demand (e.g. Bouis and Haddad, 1992; Salois et al., 2012; Green et al., 2013[3]; Ogundari and Abdulai, 2013; Zhou and Yu, 2014). No time frame regarding the publication date of primary studies was imposed. In total 89 candidate studies were identified, of which 27 had already been included in earlier review studies, while the remaining 62 concern new records, the majority of them identified through AJOL.

A further selection was made based on the relevance of the abstract to the research objectives, i.e. whether the abstract mentioned a combination of the words "food", "calorie", "nutrient", "income", and "elasticity" and whether the region of the study concerned Africa. At this stage a number of records were also excluded when a full text was not available. This screening left us with 75 articles. Next, to avoid problems of comparability between income elasticity estimates, we only maintained studies providing unit-free elasticity estimates of food demand with respect to income. This reduced the final sample to 66 studies. Fig. A.1 illustrates the selection process of primary studies and Appendix B lists the primary studies included in the meta-sample. Once a study was selected, a process of data extraction was initiated following a specific protocol about the attributes of the primary study and elasticity estimates to be gathered[4] (see Table 1). Where a study produced multiple income elasticities (e.g. for different food/nutrient groups, for urban and rural samples separately, using different estimation models), all estimates were included in the meta-sample,

[1] We use 'food' as a composite term for the three aspects we consider i.e. food types, calories and nutrients. In more specific instances however (e.g. in discussing results), we are explicit in differentiating food, calorie and nutrients.

[2] Given the focus on developing countries in Africa, we also specified the search terms in Portuguese, French and Spanish, besides English, although, in the event, none were located.

[3] Green et al. (2013) is not a review on income elasticities, but provides a meta-analysis of food-price elasticities. Since primary studies may estimate both price and income elasticities, we also screened the primary studies considered in this paper.

[4] It should be noted that a number of potential attributes (including demographic controls, conditional vs. unconditional elasticities, single- vs. multi-stage budgeting, type of estimator) were not considered either because many of the papers concerned did not provide sufficient details or because there was little variation across studies. For example, the presence of upward bias through indirect calorie and nutrition elasticity estimation linked to changes in quality of food consumed (Behrman and Deolalikar, 1987), was tested, but not found to be significantly different from zero. Yet, little variation (the largest part of studies using the direct method) and high multicollinearity with other study attributes, did not allow to include this attribute in the final regressions.

Table 1
List of variables included in the meta-sample.

Variables included in meta-sample	Description
Estimate and study level attributes (X)	
Income elasticity	Value of the estimates of income elasticities
Standard error	Standard error of the income elasticity estimate
Sample size	Number of observations used to estimate the income elasticity
Type of publication	Peer reviewed journal, report from international organisation, working paper/conference paper
Food group	Beverages; cereals; meat, fish, eggs; fruit and vegetables; dairy; fat and oils; tubers and starchy roots; legumes and nuts
Nutrient group	Carbohydrates, fats, minerals, vitamins, proteins
Time period	Pre-1990, 1991/1995, 1996/2000, 2001/2005, 2006/2015
Source of data	Primary or secondary data
Nature of data	Household/individual data, aggregate data
Structure of data	Time series, cross-sectional, panel data
Consumption measure	Monetary value (expenditure) or quantity
Income measure	Income data or total expenditure
Type of demand model	Single-equation, demand system
Type of estimator	LS/ML, panel data FD/FE/GMM, IV
Geographical coverage - country	Country to which the income elasticity refers to
Geographical coverage - type of area	All areas (i.e. rural and urban), rural area, urban area
Attributes obtained from external sources (Y)	
African region of the country	North, Central, East, West, South
Income level (ln)	Logarithm of Gross Domestic Product per capita (GDPpc)
Urbanisation	Percentage of population in urban areas

resulting in a total of 1,523 elasticities.

In addition to the attributes obtained directly from the primary studies, a number of variables obtained from sources external to the primary studies (e.g. World Bank, 2016) were added *a posteriori* to the meta-sample. The rationale for including these variables is that they may help explain the heterogeneity in the observed income elasticities. The variables considered include geographical characteristics of countries, countries' income levels (i.e. gross domestic product per capita), and the degree of urbanisation[5]. The country-level variables, and reasons for their inclusion, are described below and summarised in Table 1.

2.2. Country-level variables

2.2.1. Geographical and regional characteristics

Unlike Asia where rice dominates over the entire continent, the consumption of starchy staple crops in Africa differs largely between regions (FAO, 2016) according to the agro-ecological feasibility and economic profitability of the crops. Given strong habit persistence in the consumption of basic goods (Naik and Moore, 1996), present consumption can be expected to be highly determined by agricultural potential and historical price differences, even if present-day trading makes different types of staples more easily available than they were in the past. As such, maize is still the dominant staple in Eastern and Southern Africa, wheat is widely cultivated (and consumed) in North Africa, Sudan and Ethiopia, millet, sorghum and maize are important crops in the Sahel, and roots and tubers are common in Central Africa (Teklu, 1996; Macauley, 2015). But also other historical factors may explain present-day differences in consumer preferences. For example, in several West African countries, large amounts of rice were imported during the colonial period to keep food prices under control and since then rice has remained the most important staple in West-African diets (Diagana et al., 1999). To capture existing commonalities including agro-climatic characteristics, historical ties or cultural influences that may explain present-day differences in consumption, we created a regional indicator which assigns each country to one of five African regions (North, Southern, East, West and Central Africa) following the United States Statistical Divisions (UNSD) classification (Fig. 1).

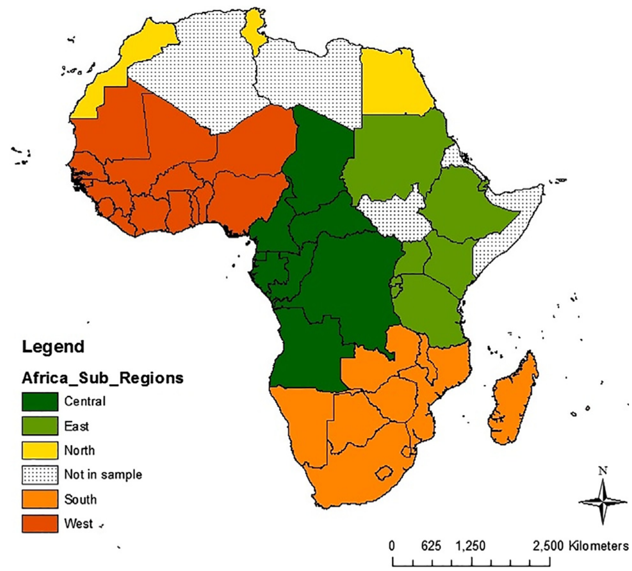

Fig. 1. African regions included in the meta-regression analysis.

2.2.2. Income level

As noted earlier, the level of a country's income influences the amount and composition of its food demand. On average, individuals in low-income countries spend nearly half of their budgets on food, while individuals living in high-income countries spend only one-fifth of total income on food (Murcott et al., 2013). As a result, lower income countries may be more responsive to volatility in food prices and income shocks especially for the high value products. To account for the role of countries' income levels in the size of the income elasticity of food demand, we include the logarithm[6] of the gross domestic product per capita (GDP pc, in constant 2005 dollar terms) from the World Development Indicators (WDI, World Bank 2016) database as a proxy for national income levels. For studies using panel and time series data, we take the average of these incomes for the period of the data in the underlying study.

2.2.3. Level of urbanisation

Urbanisation is thought to influence food demand in three main ways (Regmi and Dyck, 2001). First, urban lifestyles are typically sedentary whilst rural lifestyles are labour intensive. As a result, calorie requirements in rural diets are greater, leading to greater dependence on calorie-dense foods such as tubers, cereals and coarse grains. Second, rural livelihoods are typically based on subsistence agriculture and the

[5] Income elasticities are also likely to differ between foods that are very common (i.e. foods traditionally produced in the country) and foods perceived as luxurious or aspirational. In order to capture which types of foods can be considered as 'basic', we hoped to consider the extent to which a country's diet is dominated by certain types of foods using data for the share of a certain food in the total food consumption based on the FAO food balances for African countries. Unfortunately, this measure was only available for more recent periods and hence, due to missing values, it could not be included in the meta-regression models.

[6] Other functional forms (including per capita income and its square) have been tested to account for potential non-linearities. Except for the calorie elasticities, the logarithmic transformation was found to fit best the data and alternative functional forms did not cause any notable changes in the coefficients of the covariates or predicted elasticities. When discussing the results for the calories estimates, we include a brief discussion of the results of including GDP per capita and its square in the text.

ability of households to diversify the composition of their diets is constrained by the amount, as well as marketability, of their produce. Rural diets are therefore often dominated by households' own produce, which is often based on high yielding calorie-rich tubers, cereals and grains. In contrast, urban households typically purchase their foods and are exposed to a wider array of food choice, which may lead to greater diversity in food consumption. Thirdly, the opportunity cost of time for women in urban locations is typically higher than in rural areas, leading to a larger percentage of women working outside the home. This increases the dependence of households on foods sold outside the home (e.g. street fast foods, readymade food). In rural locations, foods are mostly home cooked as women engage in domestic occupations, often linked to agriculture. For these reasons, African countries with higher urbanisation rates are expected to face a smaller overall demand for calorie-rich foods such as tubers, cereals and grains, and greater demand for protein-based foods such as meat, fish, eggs and dairy products, and other types of foods (e.g. fruits, vegetables). We include a measure of urbanisation based on the percentage of population living in urban areas. This is high in countries such as Nigeria and South Africa, which have very large and densely populated mega-cities. Urbanisation data were taken from the WDI dataset (World Bank, 2016). For studies using panel and time series data, the average for the period of the data in the underlying study is used.

2.3. The meta-regression model

In order to analyse the relationship between income and food demand, we estimate separate meta-regressions for each type of income elasticity (food, nutrient or calorie). The specification of the models is based on the variables listed in Table 2 and can be described as follows:

$$\varepsilon_{ij} = \sum_{m=1}^{M} \beta_m X_{mj} + \sum_{n=1}^{N} \beta_n Y_{ni(c)} + \nu_{ij} \tag{1}$$

where ε_{ij} is the value of the estimate of the income elasticity, *i* identifies the elasticity estimate and *j* denotes the study to which the elasticity estimate belongs.

- X_{mj} represents the *m* variables that contain the attributes of income elasticity estimate *i* of study *j* hypothesised to explain part of the variation in the value of the income elasticity, while β_m estimates the impact of each of the *m* variables ($m = 1, 2, \ldots, M$). Some of these variables may vary within multiple-estimate studies (e.g. type of demand model), while other variables may be constant within the study (e.g. structure of data used);
- $Y_{ni(c)}$ represents the *n* country-level variables, which measure the effect of attributes due to a country *c* attributes (e.g. ln GDP per capita, urbanisation) on the income elasticity estimate *i*. β_n estimates the impact of each of the *n* country-level variables ($n = 1, 2, \ldots, N$);
- Finally, ν_{ij} is the error term, which is assumed to be normally distributed while allowing for heteroskedasticity and clustering at the study level.

The model above can be estimated using pooled Ordinary Least Squares (OLS), or panel data estimators based on random-effects and fixed-effects to take account of *between*- and *within*-study variation. The advantage of the panel data estimator is that controls for possible study-specific unobserved heterogeneity. Though the fixed-effects estimator avoids possible endogeneity bias due to correlation between unit-specific (i.e. study-specific) unobserved heterogeneity and the model covariates, it results in a great loss of variation for covariates that have little or no within-study variation (i.e. variables that are constant within studies). Since this is the case of our meta-sample, the fixed-effects estimator is not deemed appropriate. To compare pooled OLS and random-effects (RE) estimators, we use the Breusch-Pagan Lagrange Multiplier (B-P LM) test, with the null hypothesis stating that pooled OLS is appropriate. Since for most of the results pooled OLS is not rejected, we present these results in the main text. Results using the RE estimator can be found in the Appendix D.

3. Results

3.1. Description of the meta-sample

The final meta-sample includes income elasticities from 66 primary studies, covering 48 out of 54 African countries, providing a total of 1,523 estimates of food-income elasticities, 369 estimates of nutrient-income elasticities, and 123 estimates of calorie-income elasticities. Of the 66 studies included, 43 are studies which have not been included in previous meta-analyses. 11 studies were produced by international organisations (IO), 10 are working papers, while the remaining 45 are published in peer reviewed journals. Although the vast majority of studies account for a very small part of the meta-sample, four studies alone represent 58% of the whole sample, with one study (Muhammad et al., 2011) representing 21% of the whole sample.

Given the large dispersion and the presence of a number of highly implausible values among the elasticity estimates, an outlier analysis was performed using the interquartile range rule (Tukey, 1977). Income elasticity estimates outside the range $[Q1 - 3 * IQR,\ Q3 + 3 * IQR]$ were removed for nutrients, calories and for each of the food categories.[7] The resulting samples without outliers provide a total of 1,444 food-income elasticity estimates, 369 nutrient-income elasticities estimates, and 120 calorie-income elasticities estimates.

Table 2 provides a summary of the main features of the outlier-controlled sample for food-, calorie-, and nutrient-income elasticities. Of the three categories of food demand (foodstuffs, nutrients and calories), foodstuffs is by far the largest category, constituting about 75% of the observations. The number of elasticities for calorie intake contributes the lowest number of observations, about 6%, with the remaining 19% attributed to nutrients. The average income elasticity for foods is 0.61, 0.41 for nutrients, and 0.42 for calories. The coefficients of variation (CV) indicate that overall there is greater dispersion in the data for nutrient and calorie-income elasticities (0.94 and 0.84 respectively) than for food-income elasticities (0.65).

The main food groups are: beverages, cereals, dairy, fat and oil, fruits and vegetables, legumes and nuts, meat fish and eggs, and tubers and starchy root crops. As expected, food groups with the lowest mean income elasticities are those that would normally constitute the basic diet in most African countries (i.e. cereals and legumes and nuts), with average elasticities of around 0.40, whilst those with the highest elasticities would typically be more luxury products, supplementing the basic diets (i.e. meat, fish and eggs, dairy products and beverages), with average elasticities ranging from 0.80 to 1.24.

The main nutrient groups are: carbohydrates, minerals, vitamins, proteins and fats. The mean income elasticity is lowest for carbohydrates (0.23), which is in line with expectations given that carbohydrates constitute the basic components of most African diets (cereals, tubers, etc.). Income elasticities for vitamins, minerals, protein and fats are higher, which corresponds to their content being higher in the more supplementary food categories (fruits, nuts and animal-source products).

There are considerable differences in the magnitude of the income

[7] We tested the sensitivity of our results to alternative outlier selection methods (using 1.5 instead of 3 in the IQR rule (Q1: bottom quartile, Q3: upper quartile, IQR: interquartile range), or excluding the upper and lower 1% or 5% of the sample) or to using the full initial sample. The precise coefficients and significance levels on a few covariates facing high multicollinearity (i.e. covariates related to study attributes such as data structure or demand model) vary somewhat according to the outlier method used, yet differences are limited and do not affect the conclusions of the study. Results are available from the authors upon request.

Table 2
Summary statistics of meta-sample.

Income elasticities	Food-income elasticities				Nutrient-income elasticities				Calorie-income elasticities			
	Number	Share (%)	Mean	CV	Number	Share (%)	Mean	CV	Number	Share (%)	Mean	CV
Total	**1444**	**100%**	**0.613**	**0.647**	**369**	**100%**	**0.408**	**0.944**	**120**	**100%**	**0.421**	**0.836**
Type of publication												
Journal article	604	42%	0.472	1.010	295	80%	0.352	1.10	71	60%	0.388	0.707
Report	701	49%	0.726	0.396	68	18%	0.680	0.373	15	13%	0.482	0.670
Working/conf. paper	139	10%	0.659	0.423	6	2%	0.093	0.433	34	28%	0.467	1.046
Time period												
Pre-1990	21	1%	0.548	0.941	8	2%	0.195	0.283	30	25%	0.451	0.596
1991/1995	83	6%	0.802	0.370	0	n/a	n/a	n/a	20	17%	0.525	1.028
1996/2000	743	51%	0.491	0.806	218	59%	0.268	1.40	24	20%	0.332	0.918
2001/2005	507	35%	0.741	0.487	137	37%	0.657	0.419	31	26%	0.492	0.671
2006/2015	86	6%	0.738	0.417	0	n/a	n/a	n/a	3	3%	0.067	1.474
Multiple time groups	4	0%	0.825	0.434	6	2%	0.093	0.433	12	10%	0.263	0.769
African region												
Central Africa	121	8%	0.744	0.453	60	16%	0.745	0.257	6	5%	0.806	0.215
East Africa	224	16%	0.687	0.413	25	7%	0.565	0.632	49	41%	0.493	0.755
North Africa	143	10%	0.593	0.355	0	n/a	n/a	n/a	3	3%	0.527	0.346
Southern Africa	392	27%	0.681	0.613	48	13%	0.685	0.386	7	6%	0.703	0.348
West Africa	564	39%	0.513	0.861	230	62%	0.253	1.400	45	38%	0.271	1.144
Cross-country	0	0%	n/a	n/a	6	2%	0.093	0.433	10	8%	0.290	0.215
Source of data												
Both	8	0%	0.788	0.312	0	0%	n/a	n/a	1	1%	0.000	n/a
Primary	91	6%	0.531	0.897	17	5%	0.739	0.403	38	32%	0.393	0.818
Secondary	1345	93%	0.618	0.633	352	95%	0.391	0.974	81	68%	0.440	0.831
Nature of data												
Aggregate	549	38%	0.749	0.376	6	2%	0.093	0.433	13	11%	0.272	0.685
Microdata (household)	895	62%	0.530	0.816	363	98%	0.413	0.934	107	89%	0.440	0.827
Structure of data												
Cross-sectional	1348	93%	0.624	0.624	335	91%	0.426	0.927	61	51%	0.477	0.647
Panel data	77	5%	0.438	1.004	34	9%	0.226	0.839	50	42%	0.367	1.131
Time series	19	1%	0.531	0.979	0	n/a	n/a	n/a	9	8%	0.351	0.485
Type of area												
Rural/urban (both)	982	68%	0.625	0.619	232	63%	0.261	1.40	47	39%	0.313	0.813
Rural	250	17%	0.619	0.723	63	17%	0.720	0.274	47	39%	0.561	0.756
Urban	212	15%	0.551	0.674	74	20%	0.604	0.529	26	22%	0.368	0.772
Consumption measure												
Expenditure	1091	76%	0.612	0.663	278	75%	0.356	1.089	35	29%	0.543	0.838
Quantity	353	24%	0.617	0.595	91	25%	0.567	0.585	85	71%	0.372	0.777
Income measure												
Expenditure	903	63%	0.712	0.529	125	34%	0.721	0.329	64	53%	0.516	0.590
Income	541	37%	0.448	0.834	244	66%	0.247	1.397	56	47%	0.314	1.193
Demand model												
Single equation	71	5%	0.363	1.253	37	10%	0.380	0.792	87	73%	0.374	0.905
Demand system	1373	95%	0.626	0.621	332	90%	0.411	0.957	33	27%	0.548	0.661
Type of estimator												
FD/FE/GMM	4	0%	0.900	0.141	6	2%	0.093	0.433	23	19%	0.491	1.045
IV	6	0%	0.007	0.319	8	2%	0.706	0.539	12	10%	0.268	0.609
LS/ML	1427	99%	0.614	0.644	355	96%	0.407	0.945	85	71%	0.425	0.739
.	7	0%	0.729	0.543	0	0%	n/a	n/a	0	0%	n/a	n/a
Food group												
Beverages	92	6%	1.240	0.308	–	–	–	–	–	–	–	–
Cereals	363	25%	0.396	0.990	–	–	–	–	–	–	–	–
Dairy	106	7%	0.810	0.113	–	–	–	–	–	–	–	–
Fat and oil	106	7%	0.582	0.259	–	–	–	–	–	–	–	–
Fruits and vegetables	207	14%	0.620	0.457	–	–	–	–	–	–	–	–
Legumes and nuts	123	9%	0.400	1.028	–	–	–	–	–	–	–	–
Meat, fish, eggs	304	21%	0.797	0.27	–	–	–	–	–	–	–	–
Tubers and starchy root crops	143	10%	0.420	0.989	–	–	–	–	–	–	–	–
By nutrient group												
Carbohydrates	–	–	–	–	42	11%	0.228	1.407	–	–	–	–
Fats	–	–	–	–	26	7%	0.308	1.409	–	–	–	–
Minerals	–	–	–	–	108	29%	0.385	0.988	–	–	–	–
Proteins	–	–	–	–	43	12%	0.388	0.956	–	–	–	–
Vitamins	–	–	–	–	150	41%	0.498	0.762	–	–	–	–

Notes: n/a: not applicable. CV: coefficient of variation. FD/FE/GMM: First Difference/Fixed Effects/Generalized Methods of Moments. IV: Instrumental variables estimation. LS/ML: Least squares/Maximum Likelihood. Statistics are provided for the outlier-controlled sample, i.e. after removing outliers beyond the [Q1 − 3*IQR, Q3 + 3*IQR] interval.

Table 3
Results from the meta-regressions of food-income elasticities.

Variables		Model 1a	Model 2a	Model 1b	Model 2b
Type of publication (ref: Journal)	Report	0.1104*	0.1281*	0.0808	0.1038*
		(0.0596)	(0.0660)	(0.0503)	(0.0583)
	Working/conf. paper	0.3086***	0.2617***	0.2674***	0.2272**
		(0.0772)	(0.0811)	(0.0898)	(0.0944)
Food group (ref: Meat, fish, eggs)	Beverages	0.4420***	1.1067***	0.4459***	1.0564***
		(0.0530)	(0.2192)	(0.0527)	(0.2290)
	Cereals	−0.3027***	0.0891	−0.2597***	0.1122
		(0.0533)	(0.2192)	(0.0479)	(0.2079)
	Dairy	0.0187	0.1199	0.0100	0.1130
		(0.0333)	(0.1625)	(0.0361)	(0.1610)
	Fat and oil	−0.2197***	0.0103	−0.2130***	−0.0135
		(0.0340)	(0.1631)	(0.0345)	(0.1660)
	Fruits and vegetables	−0.1980***	−0.8258***	−0.1928***	−0.7720***
		(0.0619)	(0.2526)	(0.0610)	(0.2636)
	Legumes and nuts	−0.3571***	−0.8731**	−0.3201***	−0.7958**
		(0.0630)	(0.3203)	(0.0630)	(0.3195)
	Tubers	−0.2552**	−0.1906	−0.2100	−0.2187
		(0.1213)	(0.6387)	(0.1249)	(0.6934)
Source data (ref: Both)	Primary	−0.3163**	−0.2983**	−0.2750**	−0.2434
		(0.1218)	(0.1432)	(0.1275)	(0.1458)
	Secondary	−0.4520***	−0.4289***	−0.4014***	−0.3651**
		(0.1145)	(0.1458)	(0.1157)	(0.1568)
Structure data (ref: Cross-sectional)	Panel data	−0.3096**	−0.2881*	−0.3557***	−0.3361***
		(0.1492)	(0.1453)	(0.0970)	(0.1003)
	Time series	−0.0658	−0.0117	−0.3161	−0.2038
		(0.1394)	(0.1195)	(0.2278)	(0.2521)
Nature data (ref: Aggregate)	Micro	0.1402**	0.1535**	−0.0380	−0.0073
		(0.0627)	(0.0667)	(0.0971)	(0.1049)
Type of area (ref: Both)	Rural	−0.0180	−0.0043	−0.0099	−0.0022
		(0.0935)	(0.0913)	(0.0720)	(0.0739)
	Urban	−0.1186	−0.1097	−0.1403*	−0.1351*
		(0.0945)	(0.0937)	(0.0770)	(0.0779)
Income measure (ref: Expenditures)	Income	−0.1579**	−0.1523**	−0.0895	−0.0910
		(0.0652)	(0.0662)	(0.0534)	(0.0570)
Consumption measure (ref: Expenditure)	Quantity	−0.0315	−0.0069	0.0969	0.1140
		(0.0812)	(0.0820)	(0.0690)	(0.0694)
Demand model (ref: Single equation)	Demand system	0.1363	0.1322	−0.0975	−0.0923
		(0.1206)	(0.1221)	(0.0989)	(0.1008)
Country's per capita income level	ln(GDPpc)	−0.0582***	−0.0483*	−0.0829***	−0.0714***
		(0.0201)	(0.0267)	(0.0168)	(0.0258)
Country's urbanisation level	% people in cities	0.0014	0.0015	0.0008	0.0009
		(0.0015)	(0.0015)	(0.0009)	(0.0009)
African region (ref: North Africa)	Central	0.1612***	0.1726***	0.1754***	0.1802***
		(0.0466)	(0.0513)	(0.0505)	(0.0542)
	East	0.1780**	0.1853**	0.0720	0.0792
		(0.0873)	(0.0908)	(0.0623)	(0.0679)
	Southern	0.2391**	0.2515**	0.1598**	0.1703**
		(0.0964)	(0.1019)	(0.0691)	(0.0762)
	West	0.0607	0.0657	0.0549	0.0566
		(0.0497)	(0.0504)	(0.0490)	(0.0502)
Interaction food group and country's income level	Beverages * ln(GDPpc)		−0.1004***		−0.0922***
			(0.0301)		(0.0315)
	Cereals * ln(GDPpc)		−0.0603*		−0.0576*
			(0.0355)		(0.0338)
	Dairy * ln(GDPpc)		−0.0143		−0.0145
			(0.0266)		(0.0264)
	Fat and oil * ln(GDPpc)		−0.0341		−0.0296
			(0.0246)		(0.0247)
	Fruits and vegetables * ln(GDPpc)		0.1001**		0.0922**
			(0.0372)		(0.0387)
	Legumes and nuts * ln(GDPpc)		0.0858*		0.0788
			(0.0484)		(0.0482)
	Tubers * ln(GDPpc)		−0.0104		0.0008
			(0.0975)		(0.1056)

(*continued on next page*)

Table 3 (*continued*)

Variables		Model 1a	Model 2a	Model 1b	Model 2b
Time period (ref: Pre-1990)	1991/1995			0.5531**	0.5526**
				(0.2086)	(0.2281)
	1996/2000			0.1416	0.1605
				(0.1717)	(0.1924)
	2001/2005			0.1934	0.2139
				(0.1794)	(0.1980)
	2006/2015			0.3759**	0.3840**
				(0.1638)	(0.1757)
Constant		1.2005***	1.0813***	1.4558***	1.2834***
		(0.2530)	(0.2883)	(0.2998)	(0.3228)
Number of observations		1436	1436	1432	1432
Number of studies		35	35	34	34
Number of countries		47	47	47	47
Adjusted R^2		0.4304	0.4512	0.4628	0.4804
Breusch-Pagan LM test OLS vs RE (p-value)		0.0001	0.0001	0.0607	1.000

All model estimations are by pooled OLS. For models 1a, 2a (and 1b) the Breusch-Pagan LM test suggests that random effects estimation needs to be considered. Random effects results for these models are presented in Table D.1 in Appendix.
Standard errors in parentheses. Standard errors are corrected for heteroskedasticity and clustering at the study level. Note that for a few elasticity estimates no time period was identified, explaining the slightly lower number of observations in models 1b and 2b.

* Level of significance at 10%.

** Level of significance at 5%.

*** Level of significance at 1%.

elasticities across African regions. For all three categories (foods, nutrients and calories), the average income elasticity is largest for Central Africa and smallest for West Africa. Note also that West and Southern Africa are best represented in terms of number of elasticity estimates in the meta-sample.

In terms of the types of studies from which elasticity estimates are derived, 50% of all elasticity estimates were obtained from peer-reviewed journals (80% for nutrients, 60% for calories and 42% for foods). Especially for foods, a large share of elasticities was obtained from reports. The large majority of food and nutrient estimates are based on secondary, cross-sectional micro-data and use a demand system model estimated through least squares (LS) or maximum likelihood (ML). Calorie elasticities are more often based on primary and panel data and 73% of them are estimated using a single equation model. The majority of estimates (86%) in the meta-sample are for the ten-year period between 1996 and 2005. The consumption measure is more often based on expenditure data (76%) when considering food and nutrient elasticities. Calorie elasticities are mostly based on consumed quantities. In about half of the cases, total income is proxied by total consumption expenditures (56%). Only 35% of estimates are specific for urban or rural areas. For the remaining 65% estimates urban and rural consumers were pooled together.

3.2. Meta-regression analyses of calorie-, nutrient- and food-income elasticities

This section presents the results obtained from the meta-regression models for food-income elasticities in Table 3, and for nutrient- and calorie-income elasticities in Table 4. Due to limited sample size, missing data and multicollinearity issues, not all covariates included in the meta-sample (see Table 1) could be (fully) included in all specifications.[8]

The specification of the meta-regressions for food-income elasticities (see Table 3) is the most comprehensive as a result of its considerably larger sample size. Because of multicollinearity between the variable of time periods and other covariates, we present the models without (Models 1a and 2a) and with this variable (Models 1b and 2b). Table 4 presents the results for the much smaller samples of nutrient and calorie elasticities. Missing values and the very unbalanced distribution of some of the covariates across time periods and regions, led to the exclusion of several covariates in these models: time periods, African regions, source and nature of data and limited inclusion of data structure. To investigate the relationship between income and the size of income elasticities for specific food and nutrient categories, we include a version of the model specification including interaction terms between country's GDP per capita and the different types of foods (Models 2a and 2b in Table 3) and nutrients (Model 2 in Table 4). Tables 3 and 4 report the results using the pooled OLS estimator. Following the B-P LM test, we also show the results using the RE estimator for Models 1a, 1b and 2a in Appendix (see Table D.1). Figs. 2–4 present the predicted elasticities based on the regression results. The mean and median values of the predicted income elasticity estimates are also presented in Tables C.1–3 in Appendix.

3.3. Food-income elasticities

First of all, results in Table 3 confirm large differences in income elasticities according to the food group. Elasticities for beverages, meat, fish and eggs, and dairy are significantly higher than demand for other food groups, i.e. demand for these types of foods is most responsive to income changes. Demand for fat and oil, fruits and vegetables, and especially demand for basic foods such as cereals, tubers and starchy root crops, and legumes and nuts, is less elastic, and thus less responsive to income changes. These differences are illustrated in Fig. 2, which shows the average value of the predicted food-income elasticities by food group in the top panel (and reported in Table C.1 in Appendix).[9]

With respect to the country's overall income level, our results show that the size of the income elasticity becomes smaller as countries become richer. The bottom panel of Fig. 2 illustrates the relationship between the logarithm of the country's GDP per capita and income elasticities for the different food groups. Only the income elasticity for

[8] Certain study attributes typically occur simultaneously, e.g. 'FD/FE/GMM'-type estimators are typically based on 'panel data' (structure of data), which are generally 'secondary data' (source of data). Given that most of our variables are categorical, we used cross tabulations and tetrachronic correlations to assess multicollinearity between categorical and binary variables respectively. More information can be obtained from the authors upon request.

[9] Predicted estimates are calculated as the linear prediction of the income elasticities from the fitted model 2b (see Table 3).

Table 4
Results from the meta-regressions of nutrient- and calorie-income elasticities.

Variables		Nutrients - Model 1	Nutrients - Model 2	Calories - Model 1
Type of publication (ref: Journal)	Report	−0.1501	−0.1878	−0.1805*
		(0.0566)	(0.1308)	(0.1008)
	Working/conf. paper	.	.	−0.1493
				(0.0942)
Nutrient groups (ref: Proteins)	Carbohydrates	−0.0292	.	
		(0.0222)		
	Fats	0.0424	4.7118***	
		(0.0580)	(0.3006)	
	Minerals	−0.0174*	−0.1721*	
		(0.0077)	(0.0869)	
	Vitamins	0.0008	−0.5968	
		(0.0422)	(0.3736)	
Structure data (ref: Cross-sectional)	Panel data	−0.1392	.	0.1216
		(0.1786)	.	(0.0776)
	Time series	.	.	.
Type of area (ref: Both)	Rural	−0.0347	0.0841	0.2487**
		(0.1022)	(0.1085)	(0.0975)
	Urban	−0.0196	0.0990	0.1654*
		(0.0942)	(0.0927)	(0.0863)
Income measure (ref: Expenditures)	Income	−0.3600***	−0.4799**	−0.3729***
		(0.0218)	(0.1759)	(0.0857)
Demand model (ref: Single equation)	Demand system	−0.1418	−0.1257	0.1720*
		(0.0901)	(0.0939)	(0.0849)
Country's per capita income level	ln(GDPpc)	−0.1672***	−0.1758**	−0.1033
		(0.0414)	(0.0641)	(0.0836)
Country's urbanisation level	% people in cities	0.0030	0.0002	−0.0037
		(0.0027)	(0.0027)	(0.0033)
Interaction nutrient group and country's income level	Carbohydrates * ln (GDPpc)		−0.0020	
			(0.0039)	
	Fats * ln(GDPpc)		−0.7432***	
			(0.0497)	
	Minerals * ln (GDPpc)		0.0263	
			(0.0145)	
	Vitamins * ln (GDPpc)		0.1008	
			(0.0639)	
Constant		1.7140***	1.9484***	1.2676**
		(0.1293)	(0.1670)	(0.4628)
Number of observations		363	363	102
Number of studies		7	7	24
Number of countries		8	8	12
Adjusted R^2		0.3172	0.3196	0.2627
Breusch-Pagan LM test OLS vs RE (p-value)		1.000	1.000	1.000

All model estimations are by pooled OLS.
Note: The number of observations used in the meta-regressions for nutrients and calories is reduced to respectively 363 and 102 because of missing values for the covariates country's urbanisation level and country's GDP per capita. Standard errors are corrected for heteroskedasticity and clustering at the study level.
* level of significance at 10%.
** Level of significance at 5%.
*** Level of significance at 1%.

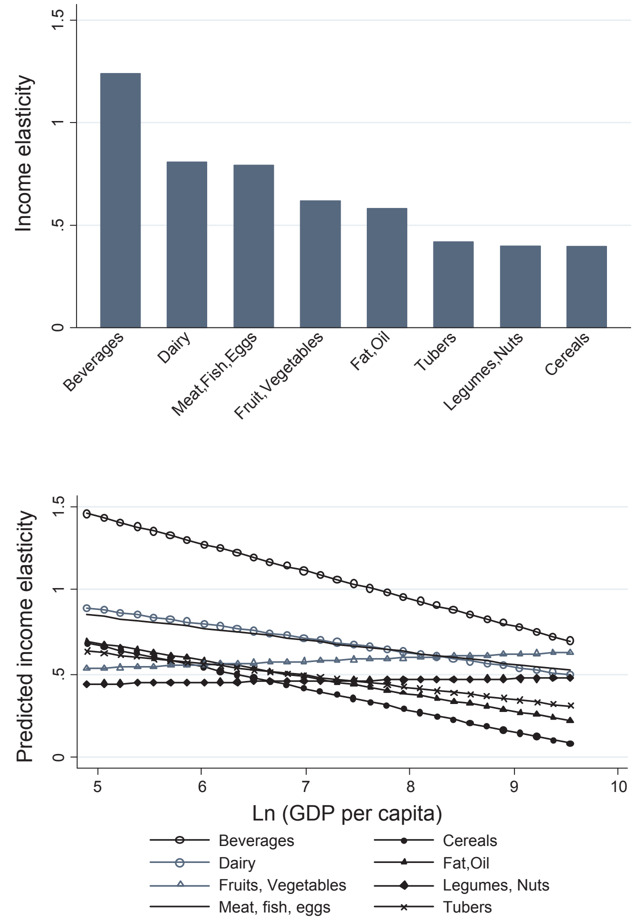

Fig. 2. Predicted income elasticities by food group (top panel) and food group and country's GDP per capita (bottom panel).

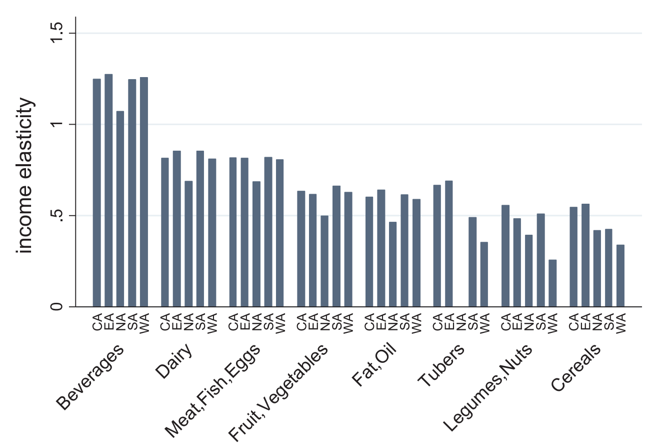

Fig. 3. Predicted income elasticities by food group and African region.

fruits and vegetables and legumes and nuts seems to increase with income growth (although the slope is small).

The country's overall urbanisation rate seems not to affect demand elasticities. Yet, once controlling for study-specific random effects (see Table D.1), there is evidence that elasticities estimated for urban consumers are significantly lower. This is in line with expectations, given that urban dwellers are generally richer and spend a lower share of their income on food items.

There are also significant differences across African regions, with higher income elasticities for Central Africa (CA) and Southern Africa (SA), followed by East (EA), West (WA) and North Africa (NA). The

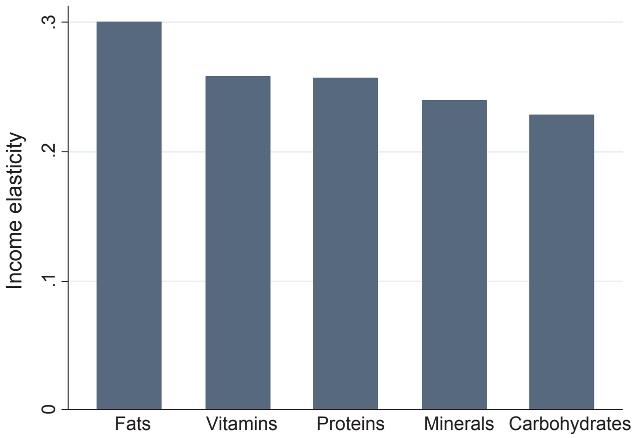

Fig. 4. Predicted income elasticities by nutrient group (top panel).

average values of the predicted food-income elasticities by food group and African region are presented in Fig. 3 (and in Table C.2 in Appendix). The predicted income elasticities differ significantly across African regions, indicating that the same relative increase in household income is likely to produce different effects in food demand across Africa.[10] Note that when controlling for random study-specific effects, differences across regions become slightly smaller.

We find no significant evidence that the magnitude of food-income elasticities has changed over time. Part of the explanation may relate to the fact that 86% of elasticity estimates are coming from two time periods only. Moreover, temporal trends may be picked up by country's GDP per capita and urbanisation rates (although the latter does not seem to be significant).

Finally, there are also some data-related and methodological factors that help explain the observed variation in food-income elasticities. Our findings suggest that elasticities are larger for working or conference papers (vs. journal articles, reports), and for studies using cross-sectional data (vs. panel data). Studies using expenditures as a proxy for income tend to get higher estimates.

3.4. Nutrient-income elasticities

Model 1 and model 2 in Table 4 report the results for the nutrient meta-regressions. Model 2 includes interaction terms to assess the relationship between the income elasticities and country's GDP per capita for the nutrient macro-components. Fig. 4 shows the average value of the predicted income elasticities by nutrient group (see Table C.3 in Appendix C) based on the results in model 1. The average predicted value is highest for fats, followed by vitamins, proteins, minerals and carbohydrates. Note however, that these figures should be read with caution. The small sample results in high standard errors, and estimates for the different nutrients categories cannot be told to be significantly different from each other. Overall, the coefficient on countries' GDP per capita is negative, confirming the earlier finding that demand elasticities for foods and their nutritional content decline with rising incomes. Interaction terms between nutrient groups and income do not show significant differences, except for the elasticity for fats, which is found to decline significantly faster when income rises compared to the other nutrient categories. Given the limited sample for nutrient-income elasticity studies, it is difficult to derive robust findings regarding the effect of study attributes. Nonetheless, some factors could be tested. The results indicate that the estimates of income elasticity tend to be higher for studies using household expenditure as a proxy for income. No statistically significant difference was found in the size of income elasticity estimates between journal articles and reports, type of area (rural or urban), and type of demand model.

3.5. Calorie-income elasticities

The last column of Table 4 also shows the results for the meta-regression of calorie-income elasticities. Using total expenditure instead of income results in significantly higher estimates. The coefficient on the logarithm of the country's income level is negative – as expected – but not significantly different from zero. Including GDP per capita and its square instead does confirm a non-linear decline in elasticity estimate for calories as incomes grow, i.e. calorie-income elasticities decline with larger incomes but at a declining rate.[11] We found no impact of the country's urbanisation level.

3.6. Sensitivity analysis

This section explores the robustness of the results by assessing (i) the degree to which they are affected by study-related heteroskedasticity (due to differences in the accuracy of the elasticity estimates) and (ii) possible publication bias. One way of addressing the first problem is to give greater weight to more reliable elasticity estimates using their respective variances (e.g. standard errors) in a weighted least squares (WLS) regression model. However, because there are only 120 income elasticity estimates with data available for respective standard errors, we adopted an inferior approach which consists of weighting each individual elasticity estimate by the square root of the sample size used (which is reported for almost all studies). The idea is that statistical power increases with sample size, that is, the t-statistic (absolute) value increases with sample size and is proportional to the square root of the degrees of freedom (e.g. Card and Krueger, 1995). The results obtained from the weighted least squares (WLS) regression are presented in Table D.2 in Appendix, and indicate that the results replicate those reported in Table 3. The sign of the coefficients is in line with the models in Table 3, but are estimated with somewhat more precision.

The second issue is potential publication bias and arises when editors, referees or researchers have preference for statistically significant results, or results that are within an expected range or in agreement with a preferred theory (e.g. Florax, 2001, Stanley, 2005). Including studies from grey literature (as we did) may help reduce the risk of publication bias, but does not guarantee a representative meta-sample since researchers themselves may also choose to report only some of their 'preferable' results for non-scientific reasons (i.e. file drawer effect). One simple sensitivity test is to consider the impact of including separate categories for type of publication (e.g. peer reviewed studies vs. 'grey' literature) or type of research sponsor (e.g. academic institution vs. international organisation). The presence of significant differences between groups may be indicative of publication bias. This was the approach followed in our study, mostly for data reasons. A more systematic test of publication bias is to include the standard error of the income elasticity in the meta-regression (e.g. Knell and Stix, 2005, Rose and Stanley, 2005). As noted above, only 120 estimates of the income elasticities included in the meta-sample also had a standard error associated with it, making it unfeasible to test for possible publication bias using more systematic approaches.

[10] Note that when interpreting the large predicted differences for some of the food groups, we should be aware of the small sample size for some categories (only 7 countries for tubers, 8 for legumes and nuts, 12 for fat and oil, and 13 for dairy). No elasticity estimates for tubers in North Africa are contained in the sample, which explains why no prediction could be made in Fig. 3.

[11] The coefficient on the linear income term is -0.0021^{***}, the coefficient on the squared income term is very small, but positive 0.000^{**}. Coefficients on the other variables are hardly affected by the choice of the functional form for income. Full regression results are available from the authors.

4. Discussion

First, our results indicate that on average, income elasticities in Africa are positive across all food and nutrient categories (Figs. 2 and 4). As income grows, consumers tend to increase the consumption of calories, nutrients and food for each of the categories. Yet, our results show considerable differences across food groups. Food items that make up basic diets, such as cereals, legumes and nuts, tubers, and (to a lesser extent) fat and oil and fruits and vegetables have lower income elasticities, while elasticities are considerably higher for animal-source foods and beverages. This trend is generally in line with expectations with respect to the nature of demand for cheaper calorie-rich products versus more sophisticated and/or aspirational foods, including animal products (Macdiarmid et al., 2016). For the nutrient-income elasticities, we find that income elasticities tend to be higher for fats, followed by vitamins, proteins and minerals, and lower for carbohydrates. Yet, the rate at which consumption increases with income is not constant. As income grows, the marginal growth rate for calories, nutrients and most food categories declines (with the exception of demand for fruits and vegetables and legumes and nuts, which become slightly more elastic with rising incomes), suggesting that food intake is getting closer to a saturation point. Fig. 2 (bottom panel) indicates that this negative effect of income on elasticities is strongest for cereals, beverages, dairy, and fat and oil. Looking at nutrient intake, Fig. 4 (bottom panel) suggests it is strongest for fats and proteins.

Second, our results provide limited evidence of a significant and systematic relationship between urbanisation rates and food-, nutrient-, and calorie-income elasticities. At the country level, we do not find that a higher degree of urbanisation significantly affects the responsiveness of food demand to changes in household income. At study-level, we do find some evidence that food-income elasticities are lower when estimated for urban compared to rural areas, which is in line with earlier findings in the literature.

Third, our results on the role of data and methodologies used across the primary studies in explaining the heterogeneity of elasticities can be compared to previous meta-analyses. In common with Ogundari and Abdulai (2013) and Zhou and Yu (2014), we find evidence of higher food-, nutrient- and calorie-income elasticities when studies use household expenditure as a proxy for income. Regarding the use of actual consumption as compared to expenditure on food (i.e. expenditure surveys), we do not find any significant impact, similarly to Zhou and Yu (2014), while Bouis and Haddad (1992) did find that estimates were smaller when using actual consumption. Our results provide some evidence for smaller food-income elasticities being obtained from journal articles compared to the 'grey' literature. As for calorie-income elasticities, we find some evidence of the opposite, which is in line with the results of Zhou and Yu (2014). We also find limited evidence suggesting that cross-sectional data lead to larger estimates compared to panel data or time series, again in line with previous studies (Ogundari and Abdulai, 2013; Zhou and Yu, 2014).

Fourth, when looking at the income elasticities across African regions, our results show non-negligible differences in terms of income elasticities for the different food types across regions (Fig. 3). North Africa tends to have the lowest or nearly lowest income elasticities, followed by West Africa, Eastern or Southern Africa (depending on the food group), while Central Africa usually has the highest mean value. It is difficult to know exactly what aspects are being captured by the geographical indicator for African regions. Some of the aspects covered will relate to differences in climate and soil, with possible implications for food production and consumption structures. However, there may be other influences captured by the geographical indicators that are influencing the results, including differences in the nature of agriculture across different regions (e.g. the share of subsistence farmers versus farm labourers in rural areas), cultural differences which influence food demand patterns (including religion), and differences in the governance of agricultural markets across African countries. In any case these results do show that this regional heterogeneity within Africa is non-negligible and call for caution when extrapolating income elasticity estimates to different countries or regions.

Finally, the construction of a comprehensive sample of all income elasticity estimates for food, nutrients and calories reveals the large heterogeneity in income elasticity estimates, even across estimates covering the same country and time period. Moreover, a large share of the elasticity estimates in this sample are for a few countries only (Nigeria, South Africa, Tanzania), while there are many countries for which none or only one elasticity estimate found, and often based on aggregate data only.

5. Conclusion

The aim of this paper was to examine the relation between income growth and food demand in Africa through a meta-analysis of food-, calorie- and nutrient-elasticities estimated in previous studies. A careful analysis of income elasticity estimates is crucial for improving the projections of future demand for foods, calories and nutrients and dietary evolutions, as well as to assess the effectiveness of income-oriented policies in the fight against undernourishment and malnutrition. We built the first meta-sample of income elasticities for Africa, using 66 primary studies and covering 48 out of 54 African countries. Since several studies reported more than one estimate, this results in a total of 1,523 food-income elasticity estimates for 7 different categories of food, 369 nutrient-income elasticity estimates for 5 types of nutrients, and 123 calorie-income elasticity estimates. Our sample shows a large heterogeneity in income elasticities, which we aim to explain by differences in data and methodology used in the primary studies, and by factors like income, urbanisation rate and the geographical location of the country within Africa, as well as the time period covered in the primary study.

The role of income-mediated policies in reducing undernutrition has been questioned by some (e.g. Behrman and Deolalikar, 1987) and income has been found to have a very limited effect on calorie intake in more affluent countries where preference for quality rather than calorific content becomes more important (Jensen and Miller, 2011; Subramanian and Deaton, 1996; Zhou and Yu, 2014). Yet our results show that almost all income elasticities reported in primary studies (for calories, as well as for each of the food- and nutrient categories) are positive, suggesting that Africa has not reached the saturation point, and that policies aimed at increasing household income can still provide an important contribution to increasing calorie consumption and reducing hunger in Africa, although at a declining rate: when income rises further, the additional contribution of income to calorie intake becomes smaller.

The positive effect of income holds for all food and nutrient categories, although we find elasticities to be typically smaller for basic calorie-rich food items (cereals, legumes, tubers) and nutrients (carbohydrates) and larger for those food and nutrient groups typically having a smaller share in expenditures. This is in line with expectations with respect to the nature of demand for cheaper calorie-rich products versus less basic and more aspirational foods. This suggests that increasing income will contribute to more diversified diets, but it is not clear whether more diverse diets will necessarily be healthier. Beverages (which tend to be high in sugar) and animal-source products are found to be the most rapidly growing food categories and although the demand for vitamins and minerals will increase with income, it will do so at a slower pace than the demand for fats and proteins. The results from our meta-analysis therefore suggest that economic growth in Africa will be associated with more nutritionally diverse diets, but also greater intakes of fats and sugars, as is observed in many rapidly growing developing countries, raising concerns of over- in addition to undernutrition. Hence, this study suggests that income-oriented policies still have a major role to play in fighting hunger and undernutrition in Africa, especially in the poorest countries. At the same time, our results point to the risk of excessive intakes of fats and sugars, as is observed in many rapidly growing developing countries, which calls for targeted policies and programs to promote nutritionally valuable and healthy diets.

Finally, our study highlights the high dispersion in income elasticity estimates for Africa and the high concentration of estimates for a small number of countries. Moreover, several methodological factors do play a significant role in the obtained elasticities. This illustrates the need for more and better food demand studies that are based on recent, detailed, country-specific and carefully collected micro-level consumption data and using up-to-standard methodologies, especially in those countries for which no or hardly any elasticity estimates exist. This will be crucial to provide reliable income elasticity estimates to improve food demand projections and to design effective agricultural, food and nutrition policies in Africa.

Disclaimer

The views expressed are purely those of the author and may not in any circumstances be regarded as stating an official position of the European Commission.

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Appendix A. Previous review studies and flow diagram for selection of primary studies

See Table A.1 and Fig. A.1.

Table A1
Previous review studies of calorie-income elasticities.

Study	Bouis and Haddad (1992)[1]	Salois et al. (2012)[1]	Ogundari and Abdulai (2013)	Zhou and Yu (2014)
No. primary studies	26	15[2]	40	90
No. elasticity estimates	Not reported	171[3]	99	387
Range	[0.01,1.18][2]	< 0–0.59 (based on study-level data)	[0.004,0.97]	[−0.23,0.99] (approximately)
Average	Not reported	Not reported	0.31	0.35
Time period	Not reported	1990–1992;2003–2005	Not reported	Not reported
Spatial coverage	Developing countries	Developing and developed countries	Developing and developed countries	Developing and developed countries

[1] These studies do not conduct a meta-analysis but do provide an overview of the empirical literature.
[2] This value is inferred from the list of primary studies and values reported in Table 1 of the respective studies.
[3] Based on the information cited in the study: "A cross-sectional sample of 171 developing and developed countries…".

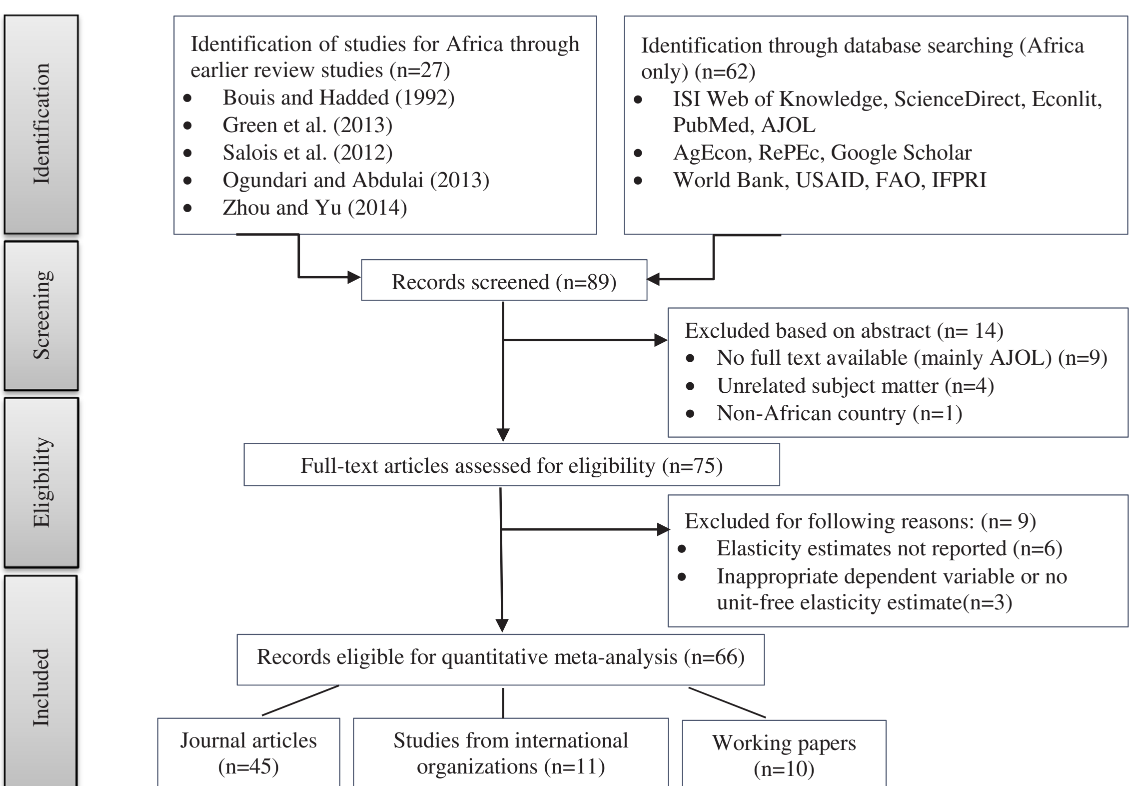

Fig. A.1. Flow diagram for selection of primary studies.

Appendix B. List of primary studies included in the meta-sample

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Appendix C. Predicted income elasticities

See Tables C.1–C.3.

Table C.1
Predicted income elasticities by food group.

Food groups	Observations	Median	Mean
Beverages	92	1.24	1.24
Cereals	362	0.36	0.40
Dairy	105	0.81	0.81
Fat and oil	106	0.59	0.58
Fruits and vegetables	207	0.61	0.62
Legumes and nuts	123	0.46	0.40
Meat, fish, and eggs	294	0.80	0.79
Tubers	143	0.32	0.42
Total	**1,432**	**0.61**	**0.61**

Table C.2
Predicted income elasticities by food group and African region.

Food groups		Central Africa	East Africa	North Africa	Southern Africa	West Africa
Beverages	Obs.	12	12	7	28	33
	Median	1.26	1.26	1.06	1.27	1.24
	Mean	1.25	1.27	1.07	1.25	1.26
Cereals	Obs.	16	46	17	77	206
	Median	0.55	0.56	0.38	0.54	0.27
	Mean	0.55	0.56	0.42	0.42	0.34
Dairy	Obs.	13	12	17	34	29
	Median	0.83	0.83	0.66	0.88	0.81
	Mean	0.81	0.85	0.69	0.85	0.81
Fat, oil	Obs.	17	14	17	25	33
	Median	0.61	0.62	0.43	0.62	0.59
	Mean	0.60	0.64	0.46	0.61	0.59
Fruits, veg.	Obs.	19	43	27	71	47
	Median	0.63	0.62	0.45	0.68	0.61
	Mean	0.63	0.62	0.50	0.66	0.63
Legumes, nuts	Obs.	6	32	10	29	46
	Median	0.56	0.50	0.39	0.48	0.21
	Mean	0.56	0.48	0.39	0.51	0.26
Meat, fish, eggs	Obs.	32	55	44	87	76
	Median	0.82	0.82	0.65	0.87	0.80
	Mean	0.82	0.81	0.68	0.82	0.81
Tubers	Obs.	6	10	.	33	94
	Median	0.67	0.68	.	0.58	0.32
	Mean	0.67	0.69	.	0.49	0.35

Table C.3
Predicted income elasticities by nutrient group.

Nutrient group	Observations	Median	Mean
Carbohydrates	42	0.23	0.23
Fats	23	0.30	0.34
Minerals	108	0.24	0.39
Proteins	40	0.26	0.41
Vitamins	150	0.69	0.50
Total	**363**	**0.26**	**0.41**

Appendix D. Additional regression results

See Tables D.1 and D.2.

Table D.1
Regression results for food groups using random effects estimator.

Variables		Model 1a (RE)	Model 2a (RE)	Model 1b (RE)	Model 2b (RE)
Type of publication (ref: Journal)	Report	0.0721	0.0828	0.0245	0.1038*
		(0.0856)	(0.0906)	(0.0816)	(0.0583)
	Working/conf. paper	0.2865**	0.2546**	0.2850***	0.2272**
		(0.1136)	(0.1134)	(0.1063)	(0.0944)
Food group (ref: Meat, fish, eggs)	Beverages	0.4442***	1.1172***	0.4454***	1.0564***
		(0.0517)	(0.2101)	(0.0516)	(0.2290)
	Cereals	−0.2604***	0.2351	−0.2574***	0.1122
		(0.0494)	(0.2107)	(0.0491)	(0.2079)
	Dairy	0.0055	0.1201	0.0059	0.1130
		(0.0372)	(0.1526)	(0.0373)	(0.1610)
	Fat and oil	−0.2361***	−0.0055	−0.2347***	−0.0135
		(0.0380)	(0.1628)	(0.0380)	(0.1660)
	Fruits and vegetables	−0.2062***	−0.7482***	−0.2050***	−0.7720***
		(0.0613)	(0.2509)	(0.0613)	(0.2636)
	Legumes and nuts	−0.3180***	−0.7431**	−0.3156***	−0.7958**
		(0.0649)	(0.3080)	(0.0648)	(0.3195)
	Tubers	−0.2112	−0.0999	−0.2089	−0.2187
		(0.1294)	(0.7465)	(0.1300)	(0.6934)

(continued on next page)

Table D.1 (*continued*)

Variables		Model 1a (RE)	Model 2a (RE)	Model 1b (RE)	Model 2b (RE)
Source data (ref: Both)	Primary	−0.1514	−0.1415	−0.2475**	−0.2434*
		(0.1787)	(0.1955)	(0.1053)	(0.1458)
	Secondary	−0.2863	−0.2762	−0.3473***	−0.3651**
		(0.1888)	(0.2087)	(0.1227)	(0.1568)
Structure data (ref: Cross-sectional)	Panel data	−0.1646	−0.1432	−0.1971	−0.3361***
		(0.1069)	(0.1083)	(0.1302)	(0.1003)
	Time series	−0.1125	−0.0735	−0.5356***	−0.2038
		(0.1759)	(0.1623)	(0.1947)	(0.2521)
Nature data (ref: Aggregate)	Micro	0.0858	0.0694	−0.1235	−0.0073
		(0.0840)	(0.0889)	(0.1313)	(0.1049)
Type of area (ref: Both)	Rural	0.0001	0.0011	0.0044	−0.0022
		(0.0598)	(0.0604)	(0.0573)	(0.0739)
	Urban	−0.1207**	−0.1211**	−0.1192**	−0.1351*
		(0.0545)	(0.0557)	(0.0550)	(0.0779)
Income measure (ref: Expenditures)	Income	−0.0799	−0.0662	−0.0455	−0.0910
		(0.1034)	(0.1020)	(0.0983)	(0.0570)
Consumption measure (ref: Expenditure)	Quantity	−0.0248	−0.0026	0.1185	0.1140
		(0.0866)	(0.0890)	(0.1099)	(0.0694)
Demand model (ref: Single equation)	Demand system	0.1572	0.1618	0.0961	−0.0923
		(0.1139)	(0.1139)	(0.1232)	(0.1008)
Country's per capita income level	ln(GDPpc)	−0.0601***	−0.0416**	−0.0619***	−0.0714***
		(0.0054)	(0.0169)	(0.0056)	(0.0258)
Country's urbanisation level	% people in cities	−0.0005	−0.0004	−0.0004	0.0009
		(0.0004)	(0.0004)	(0.0004)	(0.0009)
African region (ref: North Africa)	Central	0.1077***	0.1092***	0.1158***	0.1802***
		(0.0043)	(0.0052)	(0.0072)	(0.0542)
	East	0.0699***	0.0713***	0.0744***	0.0792
		(0.0171)	(0.0192)	(0.0187)	(0.0679)
	Southern	0.0753***	0.0788***	0.0817***	0.1703**
		(0.0134)	(0.0146)	(0.0158)	(0.0762)
	West	0.0573***	0.0567***	0.0628***	0.0566
		(0.0055)	(0.0060)	(0.0061)	(0.0502)
Interaction food group and country's income level	Beverages * ln(GDPpc)		−0.1020***		−0.0922***
			(0.0294)		(0.0315)
	Cereals * ln(GDPpc)		−0.0767**		−0.0576*
			(0.0347)		(0.0338)
	Dairy * ln(GDPpc)		−0.0164		−0.0145
			(0.0252)		(0.0264)
	Fat and oil * ln(GDPpc)		−0.0344		−0.0296
			(0.0251)		(0.0247)
	Fruits and vegetables * ln(GDPpc)		0.0867**		0.0922**
			(0.0367)		(0.0387)
	Legumes and nuts * ln(GDPpc)		0.0709		0.0788
			(0.0459)		(0.0482)
	Tubers * ln(GDPpc)		−0.0181		0.0008
			(0.1124)		(0.1056)
Time period (ref: Pre-1990)	1991/1995			0.1850	0.5526**
				(0.2505)	(0.2281)
	1996/2000			−0.0708	0.1605
				(0.1359)	(0.1924)
	2001/2005			0.0030	0.2139
				(0.1348)	(0.1980)
	2006/2015			0.1492	0.3840**
				(0.2027)	(0.1757)
Constant		1.1884***	1.0509***	1.4320***	1.2834***
		(0.2409)	(0.2568)	(0.2578)	(0.3228)
Number of observations		1436	1436	1432	1432
Number of studies		35	35	34	34
Number of countries		47	47	47	47
Overall R^2		0.3955	0.4146	0.4507	0.4935

Standard errors are corrected for heteroskedasticity and clustering at the study level.

* Level of significance at 10%.

** Level of significance at 5%.

*** Level of significance at 1%.

Table D.2
Sensitivity analysis: weighted least squares with sample size of study used as weight.

Variables		Model 1a	Model 1b
Type of publication (ref: Journal)	Report	0.0337	0.0703
		(0.0899)	(0.1457)
	Working/conf. paper	0.4200***	0.3943***
		(0.1157)	(0.1154)
Food group (ref: Meat, fish, eggs)	Beverages	0.6575***	0.6548***
		(0.1462)	(0.1483)
	Cereals	−0.2060***	−0.2038***
		(0.0468)	(0.0472)
	Dairy	0.0755	0.0759
		(0.0548)	(0.0544)
	Fat and oil	−0.1511***	−0.1504***
		(0.0303)	(0.0300)
	Fruits and vegetables	−0.1784	−0.1784
		(0.1246)	(0.1249)
	Legumes and nuts	−0.3329***	−0.3315***
		(0.0582)	(0.0590)
	Tubers	−0.3048**	−0.3017**
		(0.1222)	(0.1231)
Source data (ref: Both)	Primary	−0.4553***	−0.4066***
		(0.1353)	(0.1369)
	Secondary	−0.6677***	−0.6162***
		(0.1549)	(0.1371)
Structure data (ref: Cross-sectional)	Panel data	−0.6585***	−0.6306***
		(0.1111)	(0.1190)
	Time series	−0.0210	−1.0323***
		(0.1501)	(0.2268)
Nature data (ref: Aggregate)	Micro	0.1817	0.1768
		(0.1302)	(0.1719)
Type of area (ref: Both)	Rural	−0.1862**	−0.2014**
		(0.0832)	(0.0945)
	Urban	−0.2578***	−0.2723***
		(0.0846)	(0.0939)
Income measure (ref: Expenditures)	Income	−0.1286*	−0.1203
		(0.0686)	(0.0773)
Consumption measure (ref: Expenditure)	Quantity	−0.0521	0.0331
		(0.0943)	(0.0955)
Demand model (ref: Single equation)	Demand system	−0.0637	−0.2404*
		(0.1861)	(0.1406)
Country's per capita income level	ln(GDPpc)	−0.0877**	−0.0809*
		(0.0368)	(0.0446)
Country's urbanisation level	% people in cities	0.0051**	0.0042
		(0.0020)	(0.0025)
African region (ref: North Africa)	Central	0.3783**	0.3796**
		(0.1459)	(0.1825)
	East	0.3882***	0.3128
		(0.1369)	(0.2234)
	Southern	0.4912***	0.4241***
		(0.1208)	(0.1538)
	West	−0.0543	−0.0165
		(0.1112)	(0.1121)
Time period (ref: Pre-1990)	1991/1995		0.7001**
			(0.3297)
	1996/2000		0.5809**
			(0.2505)
	2001/2005		0.6156**
			(0.2866)
	2006/2015		0.6479***
			(0.2218)
Constant		1.5998***	1.0884*
		(0.4638)	(0.6254)
Number of observations	1427	1426	
Number of studies		34	33
Number of countries		47	47
Adjusted R^2		0.3633	0.3621

Weighted least (WLS) squares regression with each elasticity estimate weighted by the square root of sample size of the study.
Standard errors are corrected for heteroskedasticity and clustering at the study level.

* Level of significance at 10%.

** Level of significance at 5%.

*** Level of significance at 1%.

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