A Meta-Analysis of the Price and Income Elasticities of Food Demand

Fabienne Femenia
SMART-LERECO, AGRCAMPUS OUEST, INRA, Rennes, France

Abstract

Food demand elasticities are crucial parameters in the calibration of simulation models used to assess the impacts of political reforms or to analyse long-term projections, notably in agricultural sectors. Numerous estimates of these parameters are now available in the economic literature. The main objectives of this work are twofold: we seek first to identify general patterns characterizing the demand elasticities of food products and second to identify the main sources of heterogeneity between the elasticity estimates available in the literature. To achieve these objectives, we conduct a broad literature review of food demand elasticity estimates and perform a meta-regression analysis.

Our results reveal the important impacts of income levels on income and price elasticities both at the country (gross domestic product-GDP) and household levels: the higher the income is, the lower the level of elasticities. Food demand responses to changes in income and prices appear to follow different patterns depending on the global regions involved apart from any income level consideration. From a methodological viewpoint, the functional forms used to represent food demand are found to significantly affect elasticity estimates. This result sheds light on the importance of the specification of demand functions, and particularly of their flexibility, in simulation models.

Key Words

elasticities; estimation; food demand; meta-analysis

1 Introduction

Simulation models, such as general or partial equilibrium models, are often used to analyse long-term projections to assess the effects of political reforms or to shed light on a variety of issues, notably in agricultural sectors. These models use a large number of behavioural parameters, among which food demand elasticities play a crucial role (see, e.g., RUDE and MEILKE (2004) and CARPENTIER et al. (2015)). Indeed, these parameters provide information on how consumers react to income and price changes and are likely to have considerable impacts on the simulation outcomes of projection and political reform scenarios for two main reasons. First, the current global economic situation will undoubtedly evolve dramatically in the forthcoming years even if economic policies remain unchanged. This is particularly true for some developing countries in which incomes are expected to keep growing for several years. Since the level of food consumption is a key element to be analysed for one who is interested in economic projections, the impacts of income growth on household demand for food products, which strongly depend on income elasticities, must be accounted for as accurately as possible in simulation models. Second, even if agricultural policy reforms do not have strong impacts on national income levels because agriculture generally represents a small proportion of Gross Domestic Product (GDP), these reforms can have considerable impacts on agricultural prices. Demand responses to price changes are thus of crucial importance when one wishes to simulate the effects of agricultural policy reforms, and this depends on the value of food price elasticities.

Numerous price and income elasticity estimates are available in the economic literature and can be used to calibrate large-scale simulation models. However, the studies from which these estimates can be drawn use different types of data, rely on various assumptions regarding the modelling of household food demand and use different econometric estimation methods. All these sources of heterogeneity among studies may lead to significant variations in the empirical estimates reported in the literature even if these estimates are supposed to measure the same phenomenon, the responses of food demand to income or prices.

Our main objective in the present study is to investigate this issue by performing a meta-analysis to identify and quantify the main sources of heterogeneity among the demand elasticity estimates available in the literature.

As emphasized by NELSON and KENNEDY (2009), meta-analyses have been extensively used over the past decades in several areas, including economics, to synthetize information provided by empirical studies.

Some meta-analyses of food demand elasticities have been conducted with the stated objective of revealing "true" values of these parameters. GREEN et al. (2013) and CORNELSEN et al. (2016) notably conduct meta-analyses of own price and cross price elasticities for various food products to provide estimates of these parameters by country income group. CHEN et al. (2016) also use a meta-analysis with the aim of providing estimates of price and income elasticities of food demand in China. Our objective here is slightly different: we seek to understand the heterogeneity of elasticity estimates across studies to help economists to select empirical estimates of these key parameters for their simulation models. We aim at identifying the key methodological aspects of primary studies that can have an impact on the values of elasticity estimates beyond the factual elements that may affect elasticity values, such as the type of food product or the country concerned. Our work also differs from GREEN et al. (2013) and CORNELSEN et al. (2016) by focusing not only on prices but also on income elasticities, which, as explained above, can play a crucial role in long run projections and policy simulations. Furthermore, compared to these two studies, additional variables characterizing elasticity estimates are included in our analysis. We notably consider a more detailed categorization of functional forms representing food demand, household income level, and information necessary to assess publication bias, which is a pervasive issue among meta-analyses. Other meta-analyses have been conducted to examine heterogeneity in these food demand elasticities estimates with the aim of providing guidance on the study attributes to which attention should be paid. These studies generally focus only on the type of product, such as alcohol (e.g., FOGARTY, 2010; NELSON 2013a and 2013b; SORNPAISARN et al., 2013; WAGENAAR et al., 2009) or meat (GALLET, 2008 and 2010). SANTERAMO and SHABNAM (2015), MELO et al. (2015), OGUNDARI and ABDULAI (2013) and ANDREYEVA et al. (2010) are exceptions since they consider various food products. However, SANTERAMO and SHABNAM (2015), MELO et al. (2015) and OGUNDARI and ABDULAI (2013) do not explicitly consider demand elasticities of food products but calorie- and/or nutrient-income elasticities. The analysis conducted by ANDREYEVA et al. (2010) is essentially descriptive and illustrates the potential heterogeneities that can exist between price elasticities estimates without seeking to precisely identify the sources of such heterogeneity. We go deeper here by relying on a meta-regression analysis (MRA) (STANLEY and JARELL, 1989; ROBERTS, 2005). We also pay particular attention to conforming to the meta-analysis guidelines provided by the Meta-Analysis of Economics Research Network (MAER-NET) (STANLEY et al., 2013), which defines key issues related to data searches and coding and modelling strategies, that must be addressed in studies applying MRA to economics.

The first section is devoted to the description of the database of food demand elasticity estimates that we build to fulfil our objectives. In the second section, a descriptive analysis is presented to highlight several patterns characterizing own price and income elasticities in our database and to identify potential sources of heterogeneity among elasticity estimates. These sources are then statistically tested and quantified through an MRA in the third section, and conclusions are drawn in the last section.

2 The Database

The MAER-NET protocol stresses the importance of providing a complete set of information regarding the literature search, the selection of primary studies included in the meta-analysis and the coding of information collected from these studies. Due to space limitations, the main aspects of our data search and coding methods are presented in this first section, and a more detailed description is given in Appendix 1.

2.1 Data Collection

Diverse data sources are commonly used to calibrate demand functions in global economic models (VALIN et al. (2014)). Several models, such as GCAM (CLARKE et al., 2007), GLOBIOM (HAVLIK et al., 2011) or Mirage-BioF (LABORDE and VALIN, 2012), use the price elasticities provided in two reports released by the United States Department of Agriculture (USDA), SEALE et al. (2003a) and its updated version, MUHAMMAD et al. (2011), to calibrate their demand function parameters. In these reports, price and income elasticities are estimated for eight broad food categories and for a large number of countries, rendering these elasticities data well-suited for calibrating large simulation models. Economists might, however wish to use other source of elasticities when, for instance, they consider food products at a higher disaggregation level or when they wish to compare their results to those obtained with a calibration based on other estimates found in the literature. The USDA provides a literature review database (USDA, 2005), which contains this type of information and is notably used to calibrate the IMPACT model (ROBINSON et al., 2015). This database collects own price, cross price, expenditure and income demand elasticity estimates from papers that have been published and/or presented in the United States (US) between 1979 and 2005. While a large variety of products is covered at various aggregation levels, few countries are included in these data: the US is well represented, which is not surprising given the focus of the database on papers published or presented in this country, and the other elasticities included are mostly for China.

These two data sources, namely, the USDA's estimates contained in SEALE et al. (2003a) and MUHAMMAD et al. (2011) and the USDA literature review database, served as the basis for building our database. More precisely, we started with the structure of the USDA literature review database, which already includes useful information on each elasticity estimate. We reviewed the primary studies to check this information again and to ensure the consistency of the data. The elasticities estimated by SEALE et al. (2003a) and MUHAMMAD et al. (2011) were added. Then, to broaden the scope of the data, we searched for new references providing food demand elasticity estimates in the economic literature with a focus on pre-2005 studies including countries other than the US and China and on post-2005 studies whatever the country of focus. We did not limit our search to published papers: working papers, reports, and papers presented at conferences were also included. Price and income elasticity estimates of food demand reported in these papers were collected. Among own price elasticities, we distinguished uncompensated (Marshallian) price elasticities demands from compensated (Hicksian) elasticities. This distinction is important since both elasticities do not measure the same type of demand response to prices and thus cannot be considered equivalent or studied simultaneously. Uncompensated elasticities measure the impacts of a change in the price of one good by holding income and the prices of other goods constant and thus incorporate both income and substitution effects. Compensated elasticities measure the impacts of a change in the price of one good by holding consumers utility constant, i.e., they assume that price changes are compensated by income changes to maintain consumers' utility levels and do not incorporate income effects. Given the small number of compensated own price elasticities provided in the literature, we decided to focus on uncompensated price elasticities alone.

Our final database includes 3,334 own price elasticities and 3,311 income elasticity estimates collected from 93 primary studies published between 1973 and 2014. Among these studies, a significant number of papers, such as SEALE et al. (2003a) and MUHAMMAD et al. (2011), provide estimates of food demand elasticities for subsequent use to understand the structure of demands for food products or to simulate the evolution of these demands under various scenarios. While SEALE et al. (2003a) and MUHAMMAD et al. (2011) include a large number of countries[1], most of these papers focus on one particular country and/or one particular food sector. In other primary studies, food demand elasticities are estimated to address specific empirical issues, such as the impacts of advertising, product differentiation, health policies or structural changes, on the structure of food demand. Finally, several demand elasticity estimates have been collected from primary studies that focus on methodological aspects, such as the functional forms of demand models or the estimation procedures used to estimate these models. In this case, elasticities are generally estimated as an illustrative purpose to assess the proposed approach[2].

2.2 Information Included and Data Coding

A first set of information included in our database relates to the primary data that have been used to estimate demand elasticities. This information includes the type of data (time series, panel or cross-section), whether the data have been collected at the micro (household) or macro (country) level, the decade in which data have been collected, and the countries and products to which data refer. Product names as they appear in the primary studies are mapped to the following six product categories: cereals, dairy products, fruits and vegetables, oils and fats, meat and fish and other food products. As these categories are, in some cases, much broader than the product levels considered in primary studies, a variable representing the aggregation level of the primary data is also associated with each observation. Two aggregation levels are considered: "product category aggregate", which corresponds specifically to the aforementioned categories, and "product level", which refers to single

[1] SEALE et al. (2003a) and MUHAMMAD et al. (2011) use a unique model, the Florida demand model, to obtain their elasticity estimates.

[2] The complete list of references classified by the scope of the primary study is provided in Appendix 2.

products, such as bananas or apples for fruits and beef or poultry for meat. The mapping of product names, product categories and aggregation levels is presented in Appendix 3. Countries are mapped to 11 world regions according to the classification provided in Appendix 4. When applicable we also report in our data the information concerning the type (urban, rural or any type) and level of household income from which the primary data have been collected. Another approach would have involved considering simple averages of elasticities for primary studies reporting estimates for different household categories as in CORNELSEN et al. (2015), but this would have led to a loss of potentially important information.

The second type of information included in the database relates to the precision of elasticity estimates. This information is indeed necessary as recommended by the MAER-NET protocol to asses an important issue in meta-analysis, publication selection bias. Indeed, authors, reviewers and journal editors may have a preference for statistically significant results and results that are in line with the conventional view, which results in studies finding small or insignificant estimates or estimates with unexpected signs remaining unpublished (SUTTON et al. 2000; STANLEY, 2005). In our case, publication bias may cause food demand elasticities to appear much larger in absolute terms than they actually are. It is thus necessary as a first step in our meta-analysis to test for the presence of publication selection bias in our data. This can be accomplished by relying on the method proposed by EGGER et al. (1997), the PET test (precision effect test). Then, in the case that publication bias is detected, it must be accounted for in the subsequent MRA. STANLEY and DOUCOULIAGOS (2014) recommend that the PEESE (precision effect estimate with standard error) estimator be used in such cases. Both the PET test and the PEESE estimator require the use of standard errors of effect size estimates as indicators of their precision. Unfortunately, while the primary studies included in our database generally report standard errors for the estimates of the demand model parameters, few report these elements for the elasticities that are computed from these estimates[3]. Some authors (GREEN et al., 2013; CORNELSEN et al., 2015) do not evaluate publication bias because of this lack of standard error data, while others (OGUNDARI and ABDULAI (2013) and FOGARTY (2010)) focus only on primary studies in which standard errors are reported. In our case, choosing this option would have substantially reduced the size of our sample and limited the possibility of conducting an MRA. We thus relied on another approach and used inverse sample sizes or degrees of freedom (DF), which are closely related to standard errors of estimates (DAY, 1999), as measures of precision. EGGER et al. (1997) also recommends the use of one of these criteria in the absence of standard error estimates.

The last set of information included our dataset relates to the methodological aspects of elasticity estimations. We collect here all relevant information that could potentially help explain the heterogeneity among elasticity estimates. This information essentially concerns the following econometric and modelling strategies adopted in primary studies: i) the functional form of the demand system from which the elasticities are estimated; ii) the reliance on a multi-stage budgeting structure; iii) the way zero values are treated in the estimation process; iv) the use of unit values or quality adjusted prices; v) the inclusion of control variables related to household and product characteristics or time periods in the model; and vi) the econometric method used to estimate the demand model. All these aspects are discussed further in section 2.3.

3 Descriptive Analysis of the Data

After discussing how price and income demand elasticities may differ across product categories and world regions, this section highlights other potential sources of heterogeneity among estimates related to the methodological approaches adopted in the primary studies.

3.1 Heterogeneity of Elasticity Estimates across Food Products

Table 1 reports, by product category and aggregation level sub-categories, the number of observations, weighted averages and standard deviations of price and income elasticities. More weight is given to more precise estimates in the computation of averages and standard deviations.

The products that are most well-represented in our database are meat and fish followed by fruits and vegetables, cereals, other food products, dairy products, and oils and fats.

From average elasticities computed over all product aggregation levels, the demand for cereals and oils and fats appears to be less responsive to price and income than the demand for meat and fish, dairy products and fruits and vegetables, which themselves

[3] Less than 30% of estimated elasticities in our sample have associated standard error estimates.

Table 1. Elasticities - summary statistics by food product categories

	Own price elasticities			Income elasticities		
	Nb Obs.	Weighted Average	Weighted S.D.	Nb Obs.	Weighted Average	Weighted S.D.
Fruits and vegetables						
All	668	-0.61	0.69	694	0.61	0.68
Fruits and vegetables aggregate	327	-0.50	0.47	308	0.53	0.43
Product level	341	-0.71	0.79	386	0.67	0.81
Meat and fish						
All	945	-0.57	0.53	946	0.73	0.66
Meat and fish aggregate	554	-0.50	1.09	579	0.67	0.43
Product level	391	-0.66	3.85	367	0.83	0.88
Dairy products						
All	419	-0.59	0.58	412	0.72	0.60
Dairy products aggregate	295	-0.57	0.38	283	0.70	0.43
Product level	124	-0.63	0.88	129	0.75	0.86
Cereals						
All	520	-0.52	0.74	509	0.45	0.71
Cereals aggregate	306	-0.33	0.40	321	0.41	0.51
Product level	214	-0.72	0.85	188	0.50	0.95
Oils and fats						
All	338	-0.44	0.56	326	0.46	0.56
Oils and fats aggregate	282	-0.36	0.40	269	0.38	0.33
Product level	56	-0.71	0.79	57	0.75	0.88
Other food products						
All	444	-0.67	0.62	424	0.77	0.76
Other food products aggregate	307	-0.68	0.49	298	0.86	0.68
Product level	137	-0.66	0.84	126	0.58	0.81

Note: primary studies sample sizes are used as weights to compute averages and standard deviations
Source: author`s calculations

are less responsive to price and income than the demand for other food products. This ranking of food products is not surprising since the consumption of staple products is generally less responsive to price and income changes than that of "luxury" foods (TYERS and ANDERSON, 1992). The same pattern appears for elasticities estimated at the aggregate product level, whereas the ranking is very different when we consider the elasticities estimated at the product level: the demand for oils and fats appears in this case to be, on average, the most responsive to price and income changes, while the demand for dairy products is the least responsive to price changes and the demand for other food products is the least responsive to income changes. The aggregation level of the data thus appears to have an impact on price elasticity estimates. It also appears in Table 1 that elasticities estimated on more disaggregated data (product level) tend to be higher in absolute terms than those estimated for broader product categories (aggregate product level). As mentioned by EALES and UNNEVEHR (1988), this might be attributed to substitution possibilities between disaggregated products, which reduce the average own price responses of product aggregates.

We can finally observe from Table 1 that the standard deviations in elasticity estimates are relatively high compared to the average values for each type of elasticity within each category of food product considered at a specific aggregation level. This suggests the presence of additional sources of heterogeneity in elasticities, with one being location, as discussed in the following subsection.

3.2 Heterogeneity of Elasticity Estimates across Regions

Consumption patterns can differ between countries for several reasons, including differences in tastes (see, e.g., SELVANATHAN and SELVANATHAN, 1993), implying variations in demand elasticities across countries. Table 2 reports the weighted averages and standard deviations of demand elasticity estimates for the 11 world regions and six product categories that we consider.

Table 2. Elasticities - summary statistics by world regions

		Own price elasticities						Income elasticities					
		Cere-als	Dairy	Fruit and veg.	Meat	Oils and Fat	Other food	Cere-als	Dairy	Fruit and veg.	Meat	Oils and Fat	Other food
North America	Weighted average	-0.68	-0.41	-0.75	-0.62	-0.32	-0.41	0.68	0.52	0.69	0.71	0.48	0.62
	Weighted S.D.	0.61	0.66	0.74	0.49	0.47	0.58	0.89	0.67	0.91	0.78	0.72	0.83
	Nb Obs.	64	33	98	156	17	44	47	30	66	115	17	29
Latin America	Weighted average	-0.36	-0.58	-0.50	-0.54	-0.37	-0.61	0.42	0.84	0.62	0.74	0.49	0.72
	Weighted S.D.	0.41	0.50	0.43	0.36	0.46	0.30	0.46	0.60	0.56	0.53	0.51	0.59
	Nb Obs.	34	37	37	71	34	34	52	53	91	83	40	52
East Asia	Weighted average	-0.63	-0.69	-0.67	-0.66	-0.64	-0.64	0.55	0.71	0.73	0.82	0.66	0.77
	Weighted S.D.	0.82	0.84	0.73	0.84	0.78	0.90	0.86	0.79	0.78	0.76	1.09	0.76
	Nb Obs.	81	48	95	137	33	31	69	56	142	163	30	46
Asia Other	Weighted average	-0.59	-0.53	-0.64	-0.53	-0.59	-0.71	0.36	0.78	0.56	0.71	0.52	0.74
	Weighted S.D.	0.86	0.55	0.79	0.54	0.52	0.66	0.82	0.68	0.79	0.77	0.51	0.86
	Nb Obs.	122	70	157	121	47	92	116	57	134	126	35	74
European Union	Weighted average	-0.19	-0.55	-0.49	-0.49	-0.17	-0.53	0.25	0.64	0.45	0.69	0.22	0.61
	Weighted S.D.	0.41	0.65	0.64	0.51	0.21	0.38	0.46	0.63	0.56	0.79	0.27	0.52
	Nb Obs.	63	76	108	165	54	75	65	69	91	168	54	74
European Other	Weighted average	-0.42	-0.62	-0.70	-0.54	-0.42	-0.77	0.24	0.32	0.39	0.41	0.21	0.42
	Weighted S.D.	0.66	0.56	0.86	0.62	0.60	0.75	0.33	0.19	0.23	0.18	0.22	0.43
	Nb Obs.	12	12	12	18	12	12	12	12	12	18	12	12
Former Soviet Union	Weighted average	-0.32	-0.59	-0.43	-0.55	-0.34	-0.68	0.42	0.77	0.56	0.71	0.44	0.89
	Weighted S.D.	0.16	0.14	0.12	0.20	0.15	0.19	0.19	0.13	0.12	0.21	0.17	0.31
	Nb Obs.	32	32	32	64	32	32	32	32	32	64	32	32
Middle East	Weighted average	-0.58	-0.66	-0.62	-0.59	-0.56	-0.77	0.35	0.68	0.50	0.67	0.38	0.74
	Weighted S.D.	0.87	0.37	0.48	0.36	0.84	0.35	0.31	0.21	0.16	0.42	0.28	0.49
	Nb Obs.	34	34	43	62	34	50	26	26	27	55	26	28
North Africa	Weighted average	-0.33	-0.57	-0.42	-0.52	-0.34	-0.70	0.43	0.75	0.55	0.69	0.45	0.93
	Weighted S.D.	0.09	0.06	0.06	0.12	0.08	0.31	0.11	0.10	0.09	0.13	0.10	0.48
	Nb Obs.	5	5	5	10	5	5	5	5	5	10	5	5
Sub Saharan Africa	Weighted average	-0.50	-0.68	-0.56	-0.60	-0.44	-0.92	0.60	0.84	0.66	0.80	0.61	1.06
	Weighted S.D.	0.55	0.39	0.52	0.29	0.22	0.64	0.59	0.23	0.43	0.31	0.27	0.93
	Nb Obs.	67	66	75	129	64	63	79	66	88	132	69	66
Oceania	Weighted average	-0.16	-0.42	-0.30	-0.39	-0.19	-0.48	0.21	0.55	0.39	0.51	0.25	0.63
	Weighted S.D.	0.22	0.21	0.17	0.20	0.20	0.33	0.29	0.29	0.22	0.26	0.26	0.47
	Nb Obs.	6	6	6	12	6	6	6	6	6	12	6	6

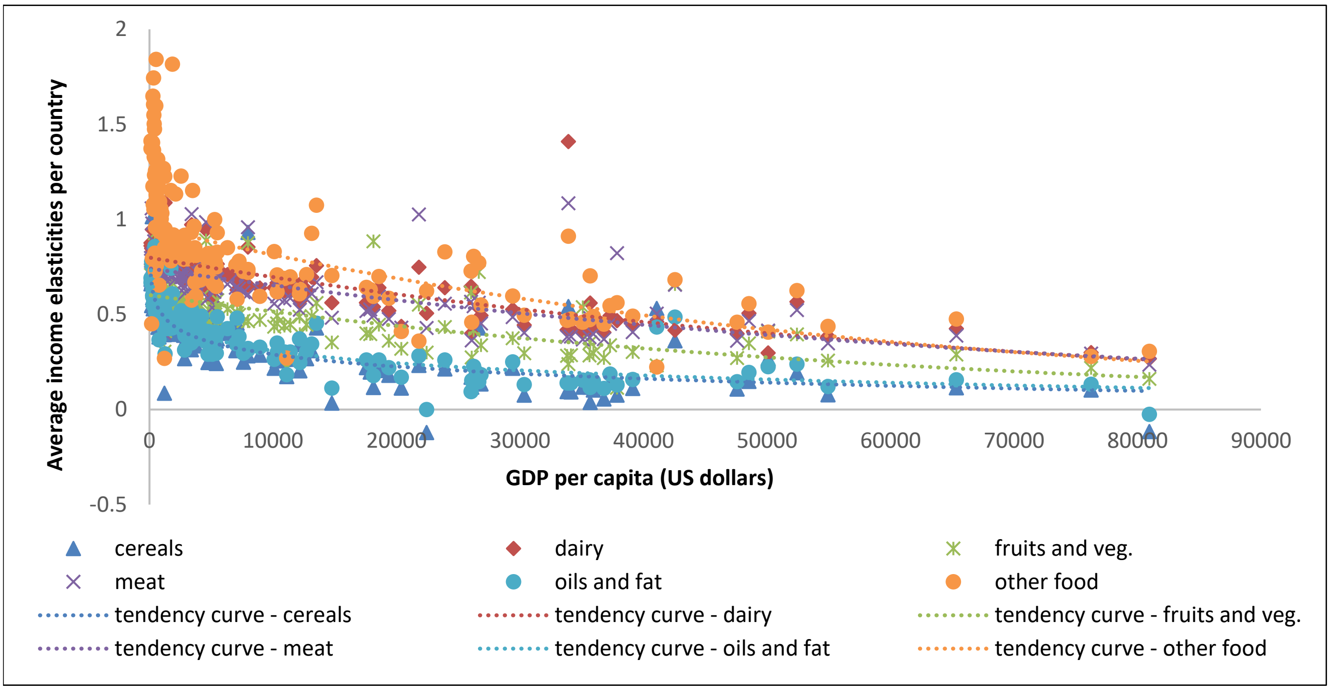
Note: primary studies sample sizes are used as weights to compute averages and standard deviations.
Source: author`s calculations

We first note that again, standard deviations of elasticity estimates are relatively high compared to their average values and for the countries that are most well-represented in the database in particular, namely, North American, Asian and European Union (EU) countries.

Table 2 shows greater variation in demand elasticities across regions for a given product than across products for a given region. Geographical aspects thus appear to have an important impact on demand elasticities. No clear regional pattern arises from the mean elasticities reported in Table 2, which is in fact not surprising given the variability in the data. One can however expect countries' income levels to have substantial impacts on demand elasticities. Indeed, income increases associated with economic development are expected to have considerable impacts on global food demand, and it is now widely recognized in the economic literature that an increase in household income not only leads to an increase in global consumption but also to a modification of consumption structures. Indeed, an income increase is expected to lead first to a decrease in the share of expenditures devoted to food consumption and second to a decrease in raw products among food expenditures. These two properties, which are formalized respectively by

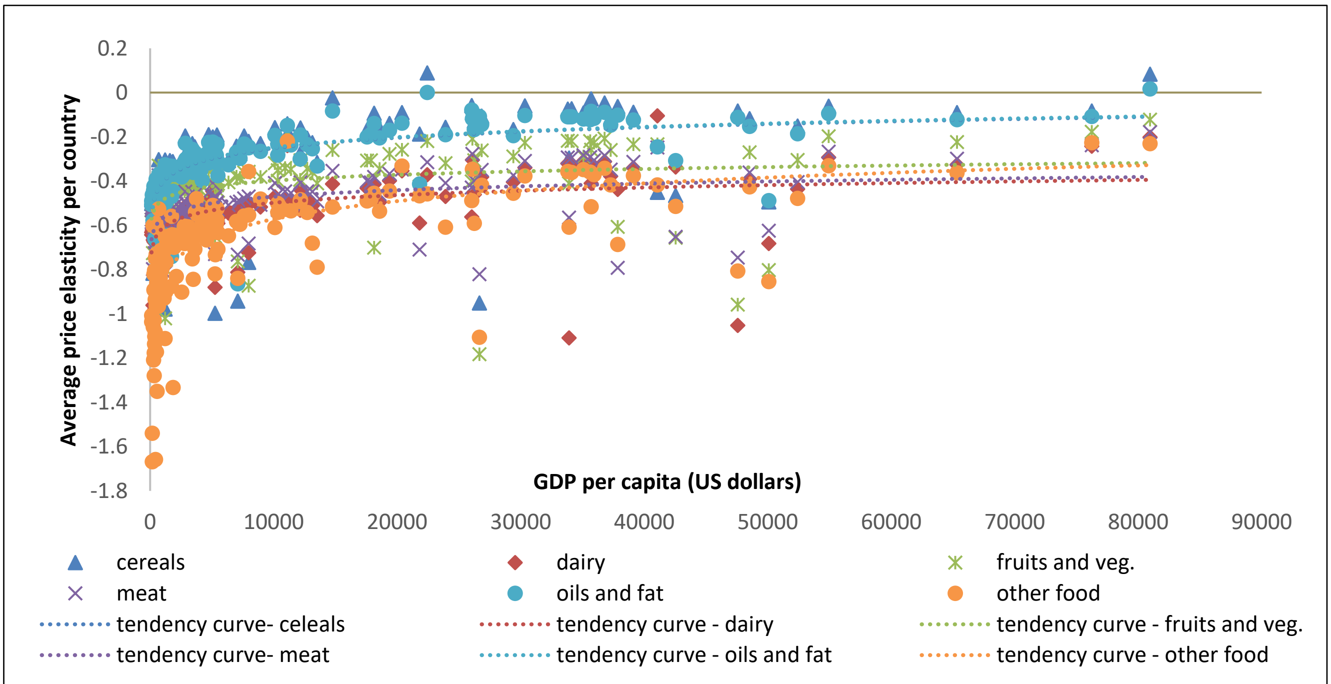
Engel's and Bennet's laws, imply that food demand becomes less responsive to income and price changes as income rises (TIMMER et al., 1983). The demand elasticities of food products, and particularly those of raw products, are thus expected to decrease (in absolute terms) with income. While not obvious in Table 2, these demand patterns clearly appear on Figures 1 and 2, in which we report the average estimated income and own price elasticities for each country with respect to their GDP per capita for 2005. These figures show that, although income and price elasticities are systematically higher for some products (e.g., meat) than for others (e.g., oils and fats), both tend to decrease with GDP per capita in absolute terms.

Figure 1. Evolution of income elasticities with GDP per capita



Source: author`s calculations

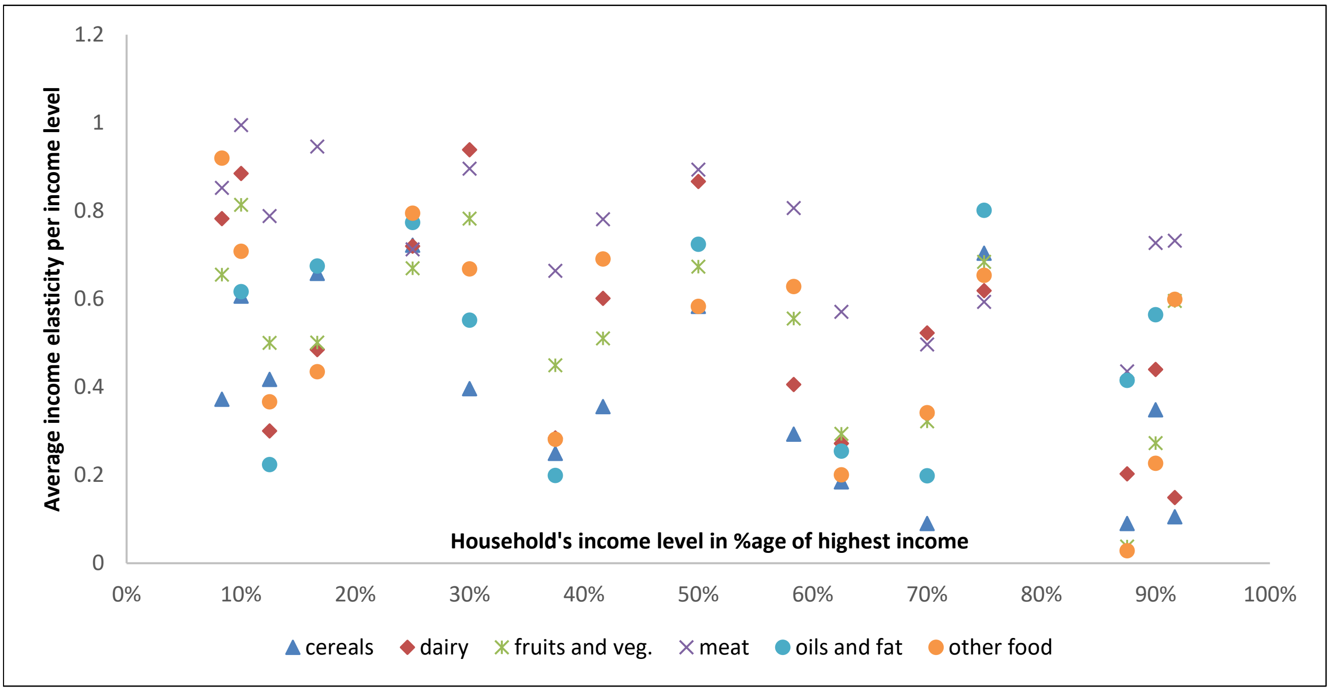
Figure 2. Evolution of price elasticities with GDP per capita



Source: author`s calculations

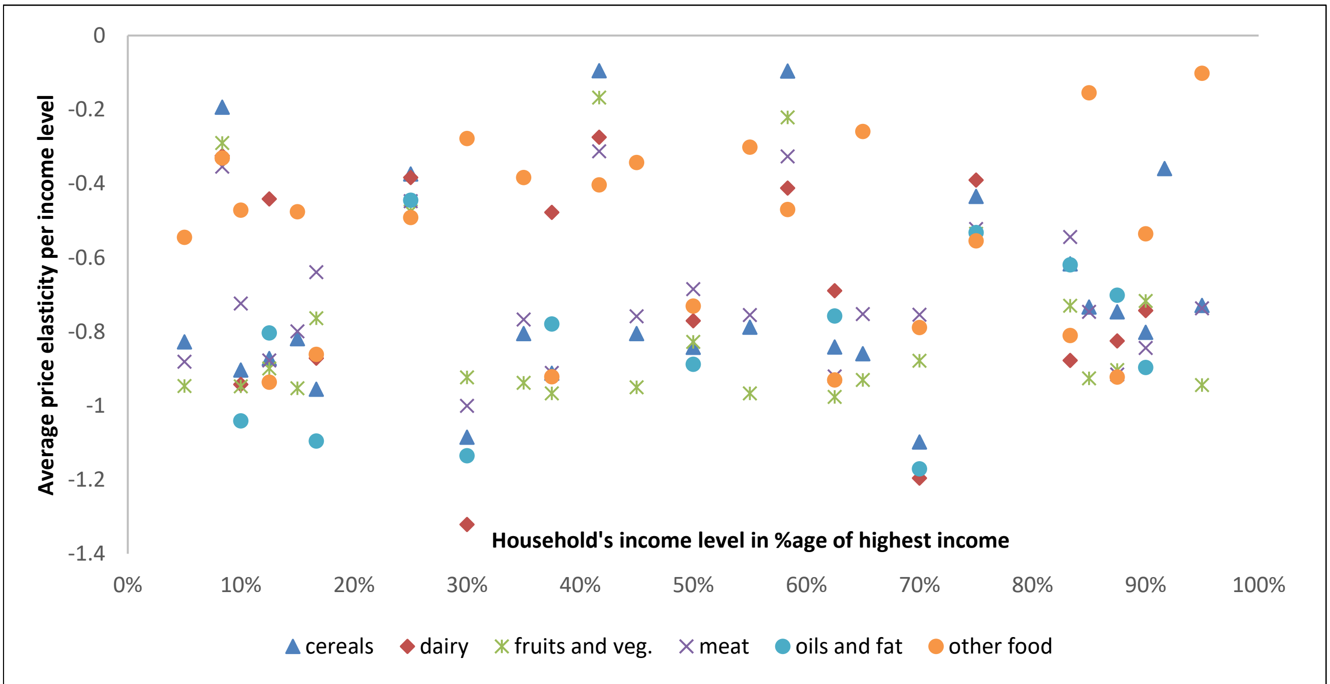
Then, price and income elasticities were estimated for different household income levels for 25 and 15 primary studies in our sample, respectively. This is illustrated on Figures 3 and 4, where income and own price elasticity estimates are reported with respect to household income levels. To make estimates from different studies comparable, income levels are represented as a percentage of the highest income considered in the study rather than as nominal income amounts. Indeed, high incomes in low GDP countries can be lower than low incomes in high GDP countries, and in most studies, incomes are not given in nominal values but in relative terms, i.e., income deciles or quartiles are considered, or a

Figure 3. Evolution of income elasticities with households' income



Source: author`s calculations

Figure 4. Evolution of price elasticities with households' income



Source: author`s calculations

distinction is made between high, medium and low incomes. A slight decrease in income elasticities with household income appears in Figure 3, but no clear pattern arises for price elasticities in Figure 4. This suggests that price elasticities vary more (with GDP) across countries than (with household income) within countries.

3.3 Methodological Sources of Heterogeneity in Elasticity Estimates

Elasticity estimates collected from different primary studies display strong levels of heterogeneity, part of which can be attributed to the data based on which they have been estimated in terms of product and country or household income. However, as illustrated by the standard deviations reported in Tables 1 and 2 and by the dispersion of data in Figures 1 to 4, a significant proportion of the heterogeneity across elasticity estimates remains unexplained by these elements. We discuss here some characteristics that are essentially related to methodological issues that differ across the studies and that might be at the root of this additional heterogeneity across study estimates. These characteristics notably concern the flexibility of the functional forms used to represent household demand, the treatment of zero values in econometric estimations of demand systems, and the definition of the "price variable" used to estimate demand systems.

Diverse functional forms representing consumer demand are used in primary studies to estimate price and income elasticities. Among them is the Rotterdam model introduced by BARTEN (1964) and THEIL (1965). The popularity of this model has already been noted by CLEMENTS and GAO (2015), who review the methodological developments that have occurred over the past fifty years in applied demand analysis and demonstrate the importance of the Rotterdam model in this respect. This model is derived in an unconventional way in the sense that it does not require the specification of a specific type of cost or utility function. Other popular demand systems, such as the Linear Expenditure System (LES) (STONE, 1954) , the Translog system (CHRISTENSEN et al., 1975), and the Almost Ideal Demand System (AIDS) (DEATON and MUELLBAUER, 1980), are indeed more traditionally derived from the optimization of specific (indirect) utility or expenditure functions. CLEMENTS and GAO (2015), however, show that these systems can actually be reformulated as differential systems relatively similar to the Rotterdam model and can thus be considered to belong to the same class of differential demand systems as that of Rotterdam[4].

Almost 7% of the primary studies included in our sample rely on the Rotterdam model. The LES and Translog systems are adopted in respectively 3% and 5% of the primary studies included in our sample. The AIDS and its linearized version, the LA-AIDS[5], are the most well-represented demand systems, with 20% and 36% of primary studies relying on them, respectively. A generalization of the AIDS, the quadratic AIDS (QUAIDS) developed by BANKS et al. (1997), is also used in 13% of the studies. In this model, budget shares are assumed to be quadratic functions of the log of income rather than linear functions, as they are in AIDS. This specification offers more flexibility in the representation of demand since income elasticities are allowed to vary with income levels. It should finally be noted that, contrary to ad hoc single equations sometimes used to estimate demand elasticities (in 5% of primary studies included in our sample), all the aforementioned demand systems are theoretically consistent since they have been built to satisfy the homogeneity, symmetry and adding-up constraints imposed by the economic theory of demand. The only theoretical property that might not necessarily be satisfied is the concavity in price of the expenditure function, which translates into the negative semidefiniteness of the Slutsky matrix. These restrictions can, however, be imposed in econometric estimations (see, e.g., MOSCHINI (1998 and 1999) and RYAN and WALES (1996)). Finally, should be noted that 11% of the primary studies use other specific models to obtain demand elasticities[6].

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[4] The CBS model (KELLER and VAN DRIEL, 1985) and the NBR model (NEVES, 1994) are two other popular models related to the Rotterdam model. Our sample, however, includes only one primary study relying on a CBS model and none that rely on an NBR model.

[5] The LA-AIDS is an approximation of the AIDS in which the linear Stone price index is used in place of the "true" AIDS price index to ease econometric estimations.

[6] Among these models are the Florida model used by SEALE et al. (2003a) and MUHAMMAD et al. (2011), the LinQuad model used by FANG and BEGHIN (2002) and FABIOSA and JENSEN (2003), the CBS model used by HAHN (2001) and the AIDADS model used by YU et al. (2003). Since these models are rarely used in our data, they have been grouped into a category termed "other" in our empirical application. Regarding the number of observations, this category is dominated by the Florida model since SEALE et al. (2003a) and MUHAMMAD et al. (2011) report 1,824 and 2,304 elasticity estimates, respectively.

Furthermore, 18% of the studies rely on multi-stage budgeting frameworks that first allocate consumer food expenditures to broad product categories or groups based on group-specific price indices and then to smaller aggregates within each category, with within-groups budget allocation performed independently. By reducing the number of parameters to be estimated this nesting structure allows one to consider demand systems with more disaggregated products. It relies on the assumption of weak separability between goods, i.e., a change in price for one product in one category is assumed to affect the demand for all products in other categories in the same way, and on the assumption of low variability in group-specific price indices with expenditures (EDGERTON, 1997). As emphasized by EDGERTON (1997) and CARPENTIER and GUYOMARD (2001), multi-stage budgeting has important implications in terms of estimated income and price elasticities since specific formulas must be used to recover total or unconditional elasticities from estimates made for group or conditional elasticities. Given that our analysis focuses on the total impacts of income or price changes on food product demand, we consider only the unconditional elasticities estimates reported in primary studies. The specific structure of multi-stage budgeting frameworks and their underlying assumptions might however have some effects on these estimated unconditional elasticities.

Another methodological difference observed across the studies concerns the treatment of corner solutions. Datasets used to estimate demand models frequently contain a significant number of zeros since not all products are consumed by all consumers. This is all the more true when products are considered at disaggregated levels and in micro-econometric studies relying individual or household data. These zero values generate corner solutions, which can be a problem for econometric estimations of demand systems. This issue can be avoided by removing zeros in datasets by excluding the corresponding observations or by considering sufficiently aggregated data. This is the case for 35% of the studies included in our database. Other studies, however, tackle the issue and account for censored demand in their econometric estimations. Different means of addressing corner solutions have been proposed in the economic literature. In particular, WALES and WOODLAND (1983) and LEE and PITT (1986), relying respectively on endogenous regime switching and virtual prices approaches, offer theoretically consistent frameworks to account for censored demands. However, these approaches are difficult to use in empirical applications, particularly when large datasets are considered. Empirical procedures have thus been developed to deal with censored demand, among which is the seminal work of HEIEN and WESSELS (1990). A few years later, the approach proposed by SHONKWILER and YEN (1999) was published and is now commonly used in the literature. In the spirit of Heckman's two-step estimator (1979), the estimator proposed by SHONKWILER and YEN (1999) involves first estimating a probit model and then conducting a regression that accounts for censoring through the introduction of correction terms that derive from the probit estimates. Although easy to implement, this estimator might lack efficiency, as do other two-step estimators (WALES and WOODLAND, 1983), and may lead to biased results in cases of distributional misspecification (SCHAFGANS, 2004). Alternative approaches based, for instance, on simulated maximum likelihood approaches (YEN et al., 2003) and semiparametric econometrics (SAM and ZHENG, 2010) have recently been proposed as means to overcome these issues.

The last methodological issue that deserves discussion relates to prices used to estimate demand systems. The datasets used to estimate demand systems do not generally explicitly contain price information mainly because prices paid by households are usually not directly observable and because goods are aggregated. A standard procedure involves using unit values (expenditures divided by quantities) as proxies for prices, but, as explained by HUANG and LIN (2000), this is not fully satisfactory since other information related to food quality is given in unit values. One solution involves following the approach proposed by DEATON (1988), which allows one to extract quality effects from unit values. In spite of the potential biases induced by the use of unit values to estimate price elasticities, 95% of the studies still use them as proxies for product prices while 5% only rely on quality-adjusted prices as proposed by DEATON (1988).

To account for these methodological issues, we introduced into the database the following four additional variables: a "model" variable with eight modalities corresponding to the various functional forms used to model demand and three dummy variables indicating whether multi-stage budgeting, the treatment of corner solutions and quality adjusted prices, have been used in the primary studies.

We also added three dummy variables to account for the fact that econometric estimations of demand systems often include several variables in addition to prices and incomes. Control variables are indeed introduced in the primary studies' econometric estimations for three main reasons. The dummy variables "hetero_indiv", "hetero_time" and "hetero_product" indicate whether demographic characteristics have been used to control for heterogeneity across households, whether time dummies and trends have been used to account for the evolution of consumer demand and preferences over time and whether product brand or advertisement characteristics have been used to control for product heterogeneity, respectively.

Finally, CORNELSEN et al. (2016) find estimation methods to have an impact on the estimated values of price elasticities. To control for this potential effect, we included in our database a variable reporting the econometric method used to conduct the estimations in the primary studies. We adopted the same classification as that used in CORNELSEN (2016) to introduce a variable taking the following four modalities: seemingly unrelated regression (SUR), ordinary least squares regression, maximum likelihood estimation and other methods. We must, however, acknowledge that the distinction between the different methods is not always straightforward since, for instance, the iterative SUR estimation method often used to impose regularity condition on demand systems is asymptotically equivalent to a maximum likelihood approach. Here, we decided to classify iterative SUR methods under the "SUR" category.

4 Meta Regression Analysis

Having described the potential sources of heterogeneity across price and income elasticity estimates found in the literature, we perform an MRA of our data to identify and quantify these sources of heterogeneity in a statistically consistent manner.

4.1 Methodology

Two sets of MRA, one for price elasticities and one for income elasticities, are performed.

The MAER-NET protocol (STANLEY et al., 2013) identifies publication selection bias, heteroscedasticity and within-studies dependence as key issues to be approached through MRA.

As explained in section 1.2, we use the PET test proposed by EGGER et al. (1997) to test for publication selection bias. When publication bias is detected, it is accounted for by introducing a measure of the precision of estimates as an explanatory variable in the MRAs in line with the method proposed by STANLEY and DOUCOULIAGOS (2014).

Heteroscedasticity issues may arise during MRA because the variances of effect size estimates vary from one primary study to another for several reasons, including differences in sample size, sample observations or estimation procedures (NELSON and KENNEDY, 2009). One straightforward means to account for this heteroscedasticity involves using a weighted least square (WLS) approach and to give more weight to the more precise estimate, i.e., to elasticity estimates with the lowest level of estimated variance. However, as noted above, very few studies included in our sample report variance in price and income elasticity estimates. We thus use primary studies' sample sizes as proxies to these variances, which is a common procedure used in MRA studies and notably in environmental economics (NELSON and KENNEDY, 2009).

Other issues can arise in the presence of correlations of effect size estimates within and between primary studies. Indeed, our data contain several elasticity estimates collected from each primary study. However, if most characteristics distinguishing estimates from the same study (product category, household income level, demand functional form, econometric estimation method, etc.) are introduced as explanatory variables and thus are controlled for in our MRAs, some unobservable characteristics may give rise to correlated error terms across elasticities collected from the same primary study. In the same way, primary studies conducted by the same author may share unobservable characteristics and may lead to between studies correlations. To overcome this issue, we follow the same approach that was used by DISDIER and HEAD (2008) and CIPOLLINA and SALVATICI (2010) and introduce random study/author effects into the MRA models. This results in the generation of mixed-effect models, which can be defined as multilevel regression models (BATEMAN and JONES, 2003) and are formally expressed as:

$$\theta_{ij} = \alpha_0 + \sum_{k=1}^{K} \alpha_k X_k + u_i + \varepsilon_{ij} \qquad (1)$$

where θ_{ij} is the dependent variable and denotes the j-th (price or income) elasticity estimate collected from the *i*-th primary study (or *i*-th author), α_0 is a fixed intercept and α_k ($k \in \{1, \dots, K\}$) is the fixed effect coefficient associated with K explanatory variable X_k ($k \in \{1, \dots, K\}$). ε_{ij} is normally distributed with constant variance and can be interpreted as a sampling error term. u_i is a random study (or author) effect that is normally distributed with constant variance independent of ε_{ij} and is assumed to be uncorrelated with the explanatory variables. Adding this random effect to the MRA model allows one to account for correlations between elasticity estimates of primary studies/authors (NELSON and KENNEDY, 2009)[7]. In this way, we also depart from the assumption that, conditional on the observed characteristics represented by the explanatory variables, all primary studies estimate exactly the same level of elasticity. Here, elasticity estimates are assumed to be comparable but not exactly the same across studies/authors (NELSON, 2013a), and the primary studies included in our data are assumed to form a random sample of a universe of potential studies (BORENSTEIN et al., 2010). The soundness of this assumption was notably underscored by HIGGINS and THOMPSON (2002), who clearly argue for the introduction of random effects into MRA models. NELSON and KENNEDY (2009) assert that mixed models may lead to bias fixed effect coefficient estimates if random effects are correlated with one or more explanatory variables. We assume that this is not the case here, which appears to be a reasonable assumption given that most of our explanatory variables are dummies representing characteristics that are not associated with only one author or study. Additionally, NELSON and KENNEDY (2009: 358) conclude that "the advantages of random-effects estimation are so strong that this estimation procedure should be employed unless a very strong case can be made for its appropriateness".

4.2 Test for Publication Bias

PET tests are performed to check for the presence of publication bias in our data. These tests involve regressing elasticity estimates on an inverse indicator of their precision. The following two sets of regressions are performed: one for price and one for income elasticities. Given the lack of standard errors of effect size estimates included in our data, we consider two alternative indicators of their precision including the inverse square root of the primary sample size and the inverse square root of DF. STANLEY and DOUCOULIAGOS (2014) also recommend the use of WLS regressions with inverse standard errors as weights to deal with heteroscedasticity issues. We follow their proposed approach and use as weights the square roots of sample sizes or DF depending on which indicator we use for the regression.

Estimation results are reported in Table 3. We find that the coefficients associated with the inverse precision criteria are significantly estimated in all cases, implying that publication selection bias exists in our data both for price (second and third columns of Table 3) and for income (fourth and fifth columns of Table 3) elasticities. Inverse precision indicators actually appear to have a positive (resp. negative) impact on price (resp. income) elasticity estimates reported in the literature, i.e., to significantly lower the values of elasticities in absolute terms. It should also be noted that all constant terms are significantly estimated and have the expected signs, which are negative for price elasticities and positive for income elasticities, implying that food demand elasticities genuinely differ from zero beyond publication bias (EGGER et al., 1997; STANLEY, 2008). Finally, all these results are robust to the selection of primary sample sizes (second and fourth columns of Table 3) or DF (third and fifth columns of Table 3) as a precision indicator.

Table 3. Test for publication bias - estimation results

	Price elasticities		Income elasticities	
	Model (1)	Model (2)	Model (1)	Model (2)
Intercept *(test for genuine true effect)*	**-0.78 (0.004)**	**-0.78 (0.01)**	**0.73 (0.01)**	**0.73 (0.01)**
Inverse square root of primary sample size (*test for publication bias*)	**7.80 (1.23)**	-	**-4.75 (1.35)**	-
Inverse square root of degrees of freedom (*test for publication bias*)	-	**7.67 (1.23)**		**-4.67 (1.34)**
N	3334	3334	3311	3311
R^2	0.0119	0.0115	0.0037	0.0037

Note: Model (1): inverse square root of sample size used as proxy to standard error – Model (2:) Inverse square root of DF used as proxy to standard error.
Source: author`s calculations

Publication bias is accounted for in subsequent MRAs by using an equivalent of the PEESE estimator proposed by STANLEY and DOUCOULIAGOS (2014), in which inverse sample sizes are used as proxies to the variances of estimates.

[7] The variance-covariance matrix of the composite error term of the model ($u_i + \varepsilon_{ij}$) is block-diagonal allowing for within-study (or within) author correlations.

4.3 Estimation Results

The mixed-effect MRA models are estimated using the *proc mixed* Maximum Likelihood method implemented with SAS software.

Five quantitative variables and 14 nominal variables are used as explanatory variables in the MRAs. The five quantitative variables are the inverse squared root of primary sample sizes used to correct for publication bias, the country's GDP, the household income level and the two time trends corresponding to the publication date of the primary studies and to the decade of the data used to estimate elasticities. The 14 nominal explanatory variables are listed in Table 4. Most of these variables have already been discussed in section 2 except for the "Urban *vs* rural households" variable, which indicates whether the elasticity has been estimated for an urban population, a rural population or the general population without distinctions made between rural and urban areas. For each nominal variable, the modality serving as a baseline reference is highlighted in Table 4.

Estimation results are presented in Table 5 for price elasticities and in Table 6 for income elasticities. In both tables, the second column (Model (1)) reports the estimated coefficient of our "baseline" mixed effect MRA model. In this model, random primary study effects are included, publication bias is accounted for by using the inverse primary sample sizes as explanatory variables, and sample sizes are also used as weights to correct for heteroscedasticity issues. The other columns of Tables 5 and 6 report the results of estimations that have been conducted to test the

Table 4. Descriptive statistics of the variables introduced in the meta-regression - summary statistics

	Own price elasticities		Income elasticities	
	Average elasticity	Nb Obs	Average elasticity	Nb Obs
Type of data				
Panel	-0.72	129	0.66	80
Cross section	-0.58	2804	0.63	2900
Time series	-0.66	401	0.69	331
Data level				
Individual	-0.70	1154	0.70	1153
Country	-0.47	2180	0.59	2158
Product				
Dairy	-0.59	419	0.72	412
Fruits and vegetables	-0.61	668	0.61	694
Meat and fish	-0.57	945	0.73	946
Oils and fats	-0.44	338	0.46	326
Other food products	-0.67	444	0.77	424
Cereals	-0.52	520	0.45	509
Product aggregation level				
Product level	-0.68	1263	0.69	1253
Aggregate level	-0.49	2071	0.60	2058
Region				
Latin America	-0.50	247	0.65	371
East Asia	-0.66	425	0.73	506
Asia Other	-0.60	609	0.59	542
European Union	-0.43	541	0.52	521
Europe Other	-0.57	78	0.34	78
Former Soviet Union	-0.49	224	0.64	224
Middle East	-0.64	257	0.57	188
North Africa	-0.49	35	0.63	35
Sub-Saharan Africa	-0.61	464	0.75	500
Oceania	-0.33	42	0.43	42
North America	-0.61	412	0.65	304
Urban *vs* rural households				
Urban	-0.62	360	0.64	346
Rural	-0.62	321	0.76	385
No distinction	-0.55	2653	0.61	2580

	Own price elasticities		Income elasticities	
	Average elasticity	Nb Obs	Average elasticity	Nb Obs
Demand model				
LA-AIDS	-0.71	503	0.82	388
AIDS	-0.84	575	0.79	229
QUAIDS	-0.78	449	0.64	319
Rotterdam	-0.44	33	0.34	36
Translog	-0.71	65	0.97	61
Single equation	-0.90	49	0.51	68
Other	-0.46	1883	0.58	1990
CES or LES	-0.31	243	0.55	220
Zero demands accounted for				
Yes	-0.77	335	0.68	283
No	-0.54	2999	0.63	3028
Prices adjusted for quality				
Yes	-0.62	165	0.80	200
No	-0.57	3191	0.62	3111
Individuals' characteristics included				
Yes	-0.57	2933	0.62	2735
No	-0.64	401	0.71	576
Products' characteristics included				
Yes	-0.58	24	0.99	16
No	-0.57	3310	0.64	3295
Time variables included				
Yes	-0.84	308	0.71	344
No	-0.55	3026	0.63	2967
Multi-stage budgeting				
Yes	-0.55	2356	0.58	2082
No	-0.64	978	0.72	1229
Econometric method				
Least Square regression	-0.41	295	0.62	337
SUR	-0.73	685	0.74	577
Other method	-0.74	248	0.70	315
Maximum Likelihood	-0.50	2106	0.60	2082

Source: author`s calculations

sensitivity of our results to the specifications of Model (1). More precisely, the third column (Model (2)) reports estimation results obtained without accounting for publication bias. The fourth column (Model (3)) reports estimation results obtained by using DF instead of sample sizes to weight observations. In Model (4), random author effects are included instead of random study effects, and in Model (5), both random study and author effects are included, with the study effect being nested within the author effect. Model (6) is a fixed effect-size MRA, i.e., no random effects are introduced to account for correlations between elasticity estimates within primary studies or authors. Models (7) and (8) are estimated to test the sensitivity of our results to the treatment of outliers. Indeed, as did CORNELSEN et al. (2015), we considered price and income elasticities that ranged outside three standard deviations of their respective averages as outliers and excluded them from our sample. Model (7) is estimated for a sample for which outliers are treated by using another approach, which is a trimming method similar to that used by Nelson (2013). The trimming method involves excluding 10% of observations from the sample, i.e., the largest elasticities (2.5% of the observations), the smallest elasticities (2.5%), the elasticities with largest standard errors (or the smallest sample sizes in our case) (2.5%) and the elasticities with lowest standard errors (or the largest sample sizes in our case) (2.5%). This method leads to the exclusion of 307 price elasticities and 287 income elasticity estimates compared to 63 and 41 estimates, respectively, that were excluded with the "three standard deviations rule". Finally, Model (8) is estimated for a sample for which no outliers are excluded.

Several findings from the estimation results of Model (1) shown in Tables 5 and 6 can be highlighted.

First, GDP per capita has a significant and negative impact on income elasticities and a positive impact on uncompensated price elasticities, meaning that both elasticities decrease in absolute terms with GDP per capita. Household income level also has a significant and negative impact on income elasticities within countries, which confirms the relevance of using this information rather than considering average elasticities computed across all household income levels, as in CORNELSEN et al. (2015). The decrease in income elasticities with income levels is indeed in accordance with economic theory related to Engel's law (see, e.g., PINSTRUP-ANDERSEN and CAICEDO (1978), who highlight this point). It is also not surprising that food demand becomes less responsive to price as incomes increase (see, e.g., ALDERMAN, 1986), especially for uncompensated price elasticities that by definition incorporate income effects of price changes (CLEMENTS et al., 2006). These results are also in line with the food demand elasticities estimates provided in SEALE et al. (2003a) and MUHAMMAD et al. (2011), who undertake an international comparison of food consumption patterns.

Second, the type of product involved has a significant impact on income and price elasticities: income elasticities tend to be lowest for cereals, higher for oils and fats and fruits and vegetables, and the highest for meat and dairy products. The ranking is the same for price elasticities. Once again, these results appear to be in accordance with the theory, and are in line with those of SEALE et al. (2003a) and MUHAMMAD et al. (2011), who found that for individual countries, staple food demand is less responsive to price and income than luxury food demand.

Third, some patterns emerge from the regional parameter estimates. Indeed, world regions appear to be divided into two groups. For a first group of regions (the EU, East Asia, North Africa and Oceania), the estimated "region" coefficients are not significantly different from zero in our meta-regressions, implying that in these regions' elasticities (income or price) are similar to those of the reference region, North America. In the second group of regions (Sub-Saharan Africa, Latin America, the Middle East, the Former Soviet Union, other European countries and other Asian countries), income and price elasticities tend to be higher in absolute terms than in the reference region. Since GDP per capita is controlled for in the estimation procedure, this result might be attributed to other differences between developed (the first group) and developing countries (the second group). These differences could, for instance, be related to differences in the diversification of consumption baskets tastes or to differences in tastes across countries as shown by CLEMENTS et al. (2006) through their comparison of international consumption patterns for broad product categories.

Table 5. MRA of price elasticities – estimation results

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)
Quantitative variables								
Intercept	-0.25 (0.15)	**-0.36 (0.15)**	-0.25 (0.15)	-0.16 (0.17)	-0.25 (0.15)	**-0.33 (0.06)**	-0.02 (0.15)	-0.32 (0.18)
Publication bias correction term	**-14.95 (5.73)**		**-15.20 (5.76)**	**-14.87 (5.82)**	**-14.96 (5.73)**	-1.21 (2.52)	**-49.93 (11.23)**	-8.57 (6.86)
Publication date trend (1976=1)	-0.004 (0.005)	-0.004 (0.005)	-0.004 (0.01)	-0.002 (0.003)	-0.004 (0.005)	-0.003 (0.001)	-0.010 (0.005)	-0.010 (0.01)
Data decade trend (1950's=1)	0.03 (0.03)	0.03 (0.03)	0.03 (0.03)	0.03 (0.02)	0.03 (0.03)	**0.04 (0.01)**	0.002 (0.03)	0.04 (0.03)
GDP per capita (in 1,000 US$)	**0.005 (0.0005)**	**0.005 (0.000)5)**	**0.005 (0.0004)**	**0.005 (0.0005)**	**0.005 (0.0005)**	**0.003 (0.0005)**	**0.005 (0.0004)**	**0.005 (0.0006)**
Household income level (%age of highest income)	-0.01 (0.02)	-0.01 (0.02)	-0.01 (0.02)	-0.02 (0.02)	-0.01 (0.02)	**-0.04 (0.02)**	0.02 (0.02)	-0.01 (0.03)
Nominal variables								
Type of data								
Panel	0.10 (0.16)	0.21 (0.16)	0.10 (0.16)	**-0.37 (0.15)**	0.10 (0.16)	**0.15 (0.06)**	**0.35 (0.16)**	0.07 (0.19)
Cross section	0.13 (0.15)	0.24 (0.15)	0.14 (0.15)	-0.16 (0.15)	0.13 (0.15)	**0.23 (0.06)**	**0.43 (0.15)**	0.04 (0.18)
Data level								
Individual	-0.13 (0.12)	-0.15 (0.12)	-0.13 (0.12)	-0.001 (0.13)	-0.13 (0.12)	**-0.21 (0.04)**	**-0.46 (0.13)**	-0.05 (0.15)
Product								
Dairy	**-0.13 (0.01)**	**-0.13 (0.01)**	**-0.13 (0.01)**	**-0.13 (0.01)**	**-0.13 (0.01)**	**-0.12 (0.02)**	**-0.13 (0.01)**	**-0.09 (0.02)**
Fruits and vegetables	**-0.08 (0.01)**	**-0.08 (0.01)**	**-0.08 (0.01)**	**-0.08 (0.01)**	**-0.08 (0.01)**	**-0.09 (0.01)**	**-0.07 (0.01)**	**-0.05 (0.02)**
Meat and fish	**-0.10 (0.01)**	**-0.10 (0.01)**	**-0.10 (0.01)**	**-0.10 (0.01)**	**-0.10 (0.01)**	**-0.10 (0.01)**	**-0.09 (0.01)**	**-0.14 (0.02)**
Oils and fats	0.01 (0.02)	0.01 (0.02)	0.01 (0.02)	0.01 (0.02)	0.01 (0.02)	0.02 (0.02)	0.03 (0.01)	0.03 (0.02)
Other food products	**-0.18 (0.01)**	**-0.18 (0.01)**	**-0.18 (0.01)**	**-0.18 (0.01)**	**-0.18 (0.01)**	**-0.18 (0.02)**	**-0.17 (0.01)**	**-0.17 (0.02)**
Product aggregation level								
Product level	0.03 (0.05)	0.03 (0.05)	0.03 (0.05)	-0.04 (0.05)	0.03 (0.05)	**-0.09 (0.02)**	-0.02 (0.04)	0.01 (0.06)
Region								
East Asia	-0.02 (0.04)	-0.01 (0.04)	-0.02 (0.04)	-0.005 (0.04)	-0.02 (0.04)	-0.01 (0.03)	-0.02 (0.04)	0.01 (0.05)
Asia Other	**-0.13 (0.04)**	**-0.12 (0.04)**	**-0.13 (0.04)**	**-0.13 (0.04)**	**-0.13 (0.04)**	**-0.21 (0.03)**	**-0.12 (0.03)**	**-0.13 (0.05)**
European Union	-0.04 (0.03)	-0.03 (0.03)	-0.04 (0.03)	-0.03 (0.03)	-0.04 (0.03)	**-0.10 (0.02)**	-0.03 (0.03)	-0.03 (0.05)
Europe Other	**-0.10 (0.05)**	**-0.10 (0.05)**	**-0.11 (0.05)**	**-0.10 (0.05)**	**-0.10 (0.05)**	**-0.26 (0.04)**	**-0.11 (0.05)**	-0.10 (0.07)
Former Soviet Union	**-0.11 (0.04)**	**-0.10 (0.04)**	**-0.11 (0.04)**	**-0.11 (0.04)**	**-0.11 (0.04)**	**-0.20 (0.03)**	**-0.10 (0.03)**	**-0.10 (0.05)**
Latin America	**-0.08 (0.04)**	-0.07 (0.04)	**-0.08 (0.04)**	**-0.07 (0.04)**	**-0.08 (0.04)**	**-0.15 (0.03)**	**-0.07 (0.03)**	-0.07 (0.05)
Middle East	**-0.09 (0.04)**	**-0.09 (0.04)**	**-0.10 (0.04)**	**-0.09 (0.04)**	**-0.09 (0.04)**	**-0.22 (0.03)**	**-0.09 (0.03)**	-0.10 (0.05)
North Africa	-0.10 (0.05)	-0.09 (0.05)	-0.10 (0.05)	-0.10 (0.05)	-0.10 (0.05)	**-0.19 (0.05)**	-0.09 (0.05)	-0.10 (0.07)
Sub-Saharan Africa	**-0.19 (0.04)**	**-0.18 (0.04)**	**-0.19 (0.04)**	**-0.18 (0.04)**	**-0.19 (0.04)**	**-0.28 (0.03)**	**-0.17 (0.03)**	**-0.20 (0.05)**
Oceania	-0.04 (0.05)	-0.03 (0.05)	-0.04 (0.05)	-0.03 (0.05)	-0.04 (0.05)	**-0.10 (0.05)**	-0.04 (0.04)	-0.03 (0.07)
Urban *vs* rural households								
Urban	0.03 (0.03)	0.03 (0.03)	0.03 (0.03)	0.03 (0.03)	0.03 (0.03)	**0.09 (0.02)**	0.05 (0.03)	0.03 (0.04)
Rural	-0.02 (0.03)	-0.02 (0.03)	-0.02 (0.03)	-0.01 (0.03)	-0.02 (0.03)	**0.05 (0.02)**	0.01 (0.03)	-0.01 (0.04)

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)
Demand model								
AIDS	**-0.39 (0.13)**	**-0.36 (0.13)**	**-0.39 (0.13)**	**-0.60 (0.15)**	**-0.39 (0.13)**	**-0.50 (0.04)**	**-0.32 (0.12)**	**-0.41 (0.15)**
LAIDS	**-0.43 (0.13)**	**-0.40 (0.13)**	**-0.43 (0.13)**	**-0.67 (0.15)**	**-0.43 (0.13)**	**-0.40 (0.04)**	**-0.3 (0.11)**	**-0.44 (0.15)**
QUAIDS	**-0.41 (0.13)**	**-0.39 (0.13)**	**-0.41 (0.14)**	**-0.44 (0.15)**	**-0.41 (0.14)**	**-0.44 (0.04)**	**-0.33 (0.12)**	**-0.44 (0.16)**
Rotterdam	**-0.38 (0.15)**	**-0.34 (0.15)**	**-0.38 (0.15)**	**-0.61 (0.16)**	**-0.38 (0.15)**	**-0.17 (0.07)**	-0.22 (0.14)	-0.33 (0.18)
Translog	**-0.36 (0.16)**	**-0.43 (0.15)**	**-0.35 (0.16)**	**-0.61 (0.17)**	**-0.36 (0.16)**	**-0.40 (0.05)**	-0.23 (0.15)	**-0.36 (0.18)**
Single equation	**-0.55 (0.17)**	**-0.60 (0.17)**	**-0.56 (0.17)**	**-0.60 (0.20)**	**-0.55 (0.17)**	**-0.68 (0.05)**	**-0.96 (0.17)**	**-0.7 (0.19)**
Other	**-0.32 (0.13)**	**-0.30 (0.13)**	**-0.33 (0.13)**	**-0.56 (0.15)**	**-0.33 (0.13)**	**-0.21 (0.04)**	**-0.35 (0.12)**	-0.27 (0.15)
Zero demands accounted for								
Yes	0.004 (0.07)	0.02 (0.07)	0.004 (0.07)	0.04 (0.05)	0.004 (0.07)	-0.01 (0.02)	-0.03 (0.06)	-0.04 (0.08)
Prices adjusted for quality								
Yes	-0.07 (0.06)	-0.07 (0.06)	-0.07 (0.06)	**-0.22 (0.05)**	-0.07 (0.06)	0.01 (0.03)	-0.09 (0.05)	-0.04 (0.08)
Individuals' characteristics included								
Yes	-0.15 (0.08)	-0.11 (0.08)	-0.15 (0.08)	-0.02 (0.05)	-0.15 (0.08)	-0.06 (0.03)	**-0.17 (0.07)**	-0.04 (0.1)
Products' characteristics included								
Yes	-0.14 (0.13)	-0.13 (0.13)	-0.14 (0.13)	-0.11 (0.1)	-0.14 (0.13)	-0.12 (0.07)	-0.06 (0.12)	-0.08 (0.15)
Time variables included								
Yes	-0.07 (0.06)	-0.08 (0.06)	-0.07 (0.06)	**-0.10 (0.04)**	-0.07 (0.06)	**-0.11 (0.02)**	-0.02 (0.06)	-0.05 (0.07)
Multi-stage budgeting								
Yes	0.04 (0.06)	0.04 (0.06)	0.04 (0.06)	0.002 (0.05)	0.04 (0.06)	0.02 (0.02)	-0.03 (0.05)	0.03 (0.07)
Econometric method								
Least Square regression	0.13 (0.10)	0.11 (0.1)	0.13 (0.10)	**0.23 (0.10)**	0.13 (0.10)	**0.29 (0.04)**	0.18 (0.10)	0.13 (0.12)
SUR	0.11 (0.07)	0.09 (0.06)	0.11 (0.07)	**0.34 (0.06)**	0.11 (0.07)	**0.17 (0.02)**	0.09 (0.06)	0.09 (0.08)
Other	0.08 (0.07)	0.06 (0.07)	0.08 (0.07)	**0.20 (0.07)**	0.08 (0.07)	**0.14 (0.03)**	**0.17 (0.07)**	0.03 (0.09)
Number of observations	3,334	3,334	3,334	3,334	3,334	3,334	3,090	3,397
-2LogLikelihood	-329.9	-323.2	-332.6	-308.1	-329.9	62.3	-1093.3	1978.4
Akaike' Information Criterion	-239.9	-235.2	-242.6	-218.1	-237.9	150.3	-1003.3	2068.4
Bayesian Information Criterion	-135.1	-132.6	-137.7	-132.0	-130.7	419.3	-902.1	2069.6
Variance of error terms	0.19	0.19	0.19	0.19	0.19	0.23	0.15	0.38
Variance of random effect								
Study effect	0.03	0.03	0.03		0.02	-	0.02	0.04
Author effect	-	-		0.05	0.02	-	-	-

Note: standard errors are in parentheses, parameter estimates significant at 5% are reported in bold – Model (1): "baseline" – Model (2): no correction for publication bias – Model (3): DF used to weight observations – Model (4): Random author effect – Model (5): Random author effect – Model (6): Fixed effect MRA – Model (7): Treatment of outliers by trimming method – Model (8): No treatment of outliers.

Source: author`s calculations

Table 6. MRA of income elasticities – estimation results

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)
Quantitative variables								
Intercept	0.41 (0.25)	0.23 (0.23)	0.40 (0.25)	0.35 (0.28)	0.41 (0.25)	**0.74 (0.08)**	0.13 (0.20)	**0.56 (0.27)**
Publication bias correction term	**-24.66 (6.29)**		**-23.78 (6.36)**	**-31.76 (6.48)**	**-24.66 (6.29)**	-4.67 (3.37)	10.16 (8.14)	**-17.73 (8.26)**
Publication date trend (1976=1)	0.003 (0.01)	0.01 (0.01)	0.003 (0.01)	0.01 (0.004)	0.003 (0.01)	-0.001 (0.002)	0.01 (0.01)	0.01 (0.01)
Data decade trend (1950's=1)	0.01 (0.03)	**0.01 (0.03)**	0.01 (0.03)	-0.03 (0.03)	0.01 (0.03)	**0.05 (0.02)**	-0.02 (0.03)	-0.04 (0.04)
GDP per capita (in 1,000 US$)	**-0.01 (0.0005)**	**-0.01 (0.0005)**	**-0.01 (0.0005)**	**-0.01 (0.0005)**	**-0.01 (0.0005)**	**-0.01 (0.0005)**	**-0.01 (0.0005)**	**-0.01 (0.0005)**
Household income level (%age of highest income)	**-0.19 (0.03)**	-0.21 (0.03)	**-0.19 (0.03)**	**-0.18 (0.03)**	**-0.19 (0.03)**	**-0.21 (0.03)**	**-0.11 (0.03)**	**-0.23 (0.04)**
Nominal variables								
Type of data								
Panel	-0.25 (0.25)	-0.27 (0.24)	-0.25 (0.25)	0.10 (0.21)	-0.25 (0.25)	**-0.52 (0.08)**	-0.19 (0.21)	-0.26 (0.28)
Cross section	-0.10 (0.21)	-0.11 (0.21)	-0.10 (0.21)	0.29 (0.20)	-0.10 (0.21)	-0.08 (0.07)	-0.12 (0.17)	-0.06 (0.24)
Data level								
Individual	-0.19 (0.18)	-0.07 (0.17)	-0.18 (0.18)	-0.26 (0.19)	-0.19 (0.18)	0.05 (0.06)	-0.06 (0.15)	-0.11 (0.21)
Product								
Dairy	**0.29 (0.02)**	**0.29 (0.02)**	**0.28 (0.02)**	**0.28 (0.02)**	**0.29 (0.02)**	**0.28 (0.02)**	**0.26 (0.01)**	**0.34 (0.03)**
Fruits and vegetables	**0.15 (0.02)**	**0.15 (0.02)**	**0.15 (0.01)**	**0.15 (0.02)**	**0.15 (0.02)**	**0.14 (0.02)**	**0.14 (0.01)**	**0.19 (0.02)**
Meat and fish	**0.28 (0.01)**	**0.28 (0.01)**	**0.28 (0.01)**	**0.27 (0.01)**	**0.28 (0.01)**	**0.29 (0.02)**	**0.25 (0.01)**	**0.32 (0.02)**
Oils and fats	**0.05 (0.02)**	**0.05 (0.02)**	**0.05 (0.02)**	**0.05 (0.02)**	**0.05 (0.02)**	**0.05 (0.02)**	**0.03 (0.02)**	**0.11 (0.03)**
Other food products	**0.36 (0.02)**	0.36 (0.02)	**0.36 (0.02)**	**0.36 (0.02)**	**0.36 (0.02)**	**0.34 (0.02)**	**0.33 (0.01)**	**0.44 (0.02)**
Product aggregation level								
Product level	0.07 (0.06)	0.05 (0.06)	0.07 (0.06)	0.11 (0.05)	0.07 (0.06)	**-0.06 (0.03)**	**0.18 (0.05)**	-0.01 (0.07)
Region								
East Asia	0.03 (0.05)	**0.03 (0.05)**	0.03 (0.05)	-0.005 (0.05)	0.03 (0.05)	**-0.01 (0.03)**	0.03 (0.04)	0.02 (0.07)
Asia Other	**0.15 (0.04)**	0.15 (0.04)	**0.15 (0.04)**	**0.13 (0.04)**	**0.15 (0.04)**	**-0.07 (0.04)**	**0.15 (0.04)**	0.12 (0.07)
European Union	0.04 (0.04)	**0.04 (0.04)**	0.04 (0.04)	0.01 (0.04)	0.04 (0.04)	-0.03 (0.03)	0.04 (0.03)	0.02 (0.06)
Europe Other	**0.11 (0.06)**	**0.12 (0.06)**	**0.11 (0.06)**	0.07 (0.05)	**0.11 (0.06)**	-0.09 (0.04)	**0.11 (0.05)**	0.09 (0.08)
Former Soviet Union	**0.12 (0.04)**	**0.12 (0.04)**	**0.12 (0.04)**	**0.10 (0.04)**	**0.12 (0.04)**	-0.01 (0.04)	**0.12 (0.04)**	0.10 (0.07)
Latin America	**0.09 (0.04)**	**0.09 (0.04)**	**0.09 (0.04)**	0.07 (0.04)	**0.09 (0.04)**	-0.02 (0.04)	**0.08 (0.04)**	0.07 (0.06)
Middle East	**0.10 (0.04)**	0.11 (0.04)	**0.10 (0.04)**	**0.09 (0.04)**	**0.10 (0.04)**	-0.03 (0.04)	**0.10 (0.04)**	0.08 (0.06)
North Africa	0.11 (0.06)	**0.11 (0.06)**	0.11 (0.06)	0.10 (0.06)	0.11 (0.06)	-0.02 (0.06)	**0.11 (0.05)**	0.09 (0.09)
Sub-Saharan Africa	**0.22 (0.04)**	0.22 (0.04)	**0.22 (0.04)**	**0.21 (0.04)**	**0.22 (0.04)**	**0.09 (0.04)**	**0.20 (0.04)**	**0.22 (0.06)**
Oceania	0.04 (0.06)	0.04 (0.06)	0.04 (0.06)	0.02 (0.05)	0.04 (0.06)	-0.07 (0.05)	0.03 (0.05)	0.01 (0.08)
Urban *vs* rural households								
Urban	-0.08 (0.04)	-0.07 (0.04)	-0.08 (0.04)	**-0.13 (0.04)**	-0.08 (0.04)	**-0.10 (0.03)**	**-0.09 (0.04)**	-0.04 (0.06)
Rural	0.05 (0.04)	0.05 (0.04)	0.05 (0.04)	-0.01 (0.04)	0.05 (0.04)	0.04 (0.03)	-0.004 (0.04)	0.10 (0.06)

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)
Demand model								
AIDS	0.27 (0.23)	0.30 (0.22)	0.27 (0.23)	0.10 (0.26)	0.27 (0.23)	0.07 (0.05)	**0.36 (0.18)**	0.28 (0.24)
LAIDS	0.24 (0.23)	0.26 (0.21)	0.24 (0.23)	0.06 (0.27)	0.24 (0.23)	**0.21 (0.05)**	0.31 (0.18)	0.27 (0.24)
QUAIDS	0.28 (0.23)	0.30 (0.21)	0.28 (0.22)	0.09 (0.26)	0.28 (0.23)	-0.02 (0.05)	0.31 (0.18)	0.23 (0.24)
Rotterdam	0.19 (0.24)	**0.21 (0.23)**	0.19 (0.24)	0.11 (0.28)	0.19 (0.24)	**-0.28 (0.08)**	0.10 (0.20)	0.12 (0.27)
Translog	**0.74 (0.26)**	0.59 (0.24)	**0.74 (0.26)**	**0.78 (0.28)**	**0.74 (0.26)**	**0.39 (0.07)**	**0.76 (0.21)**	**0.68 (0.28)**
Single equation	-0.04 (0.26)	0.04 (0.25)	-0.04 (0.26)	-0.38 (0.32)	-0.04 (0.26)	0.03 (0.06)	0.13 (0.21)	-0.03 (0.28)
Other	0.14 (0.23)	0.19 (0.22)	0.15 (0.23)	-0.11 (0.27)	0.14 (0.23)	**-0.16 (0.06)**	0.30 (0.18)	0.12 (0.25)
Zero demands accounted for								
Yes	-0.18 (0.10)	-0.15 (0.10)	-0.18 (0.1)	**-0.19 (0.07)**	-0.18 (0.10)	**-0.28 (0.02)**	-0.14 (0.09)	-0.21 (0.11)
Prices adjusted for quality								
Yes	0.14 (0.12)	0.16 (0.11)	0.14 (0.12)	-0.05 (0.06)	0.14 (0.12)	0.04 (0.03)	0.15 (0.09)	0.14 (0.12)
Individuals' characteristics included								
Yes	0.12 (0.11)	0.17 (0.11)	0.12 (0.11)	-0.11 (0.08)	0.12 (0.11)	-0.01 (0.03)	0.17 (0.09)	0.15 (0.12)
Products' characteristics included								
Yes	)0.22 (0.19)	0.26 (0.19)	0.23 (0.19)	**0.35 (0.16)**	0.22 (0.19)	**0.27 (0.09)**	0.12 (0.15)	**0.71 (0.21)**
Time variables included								
Yes	0.01 (0.09)	0.001 (0.09)	0.01 (0.09)	0.0007 (0.06)	0.01 (0.09)	0.02 (0.02)	-0.02 (0.07)	0.01 (0.10)
Multi-stage budgeting								
Yes	**-0.20 (0.09)**	-0.19 (0.09)	**-0.2 (0.09)**	**-0.37 (0.07)**	**-0.20 (0.09)**	**-0.27 (0.03)**	**-0.21 (0.08)**	**-0.20 (0.10)**
Econometric method								
Least Square regression	0.08 (0.13)	0.04 (0.13)	0.07 (0.13)	**0.46 (0.14)**	0.08 (0.13)	**-0.25 (0.04)**	0.03 (0.12)	0.03 (0.16)
SUR	0.06 (0.1)	0.02 (0.10)	0.06 (0.10)	**0.48 (0.09)**	0.06 (0.10)	**-0.09 (0.03)**	0.04 (0.08)	0.02 (0.11)
Other	0.06 (0.12)	-0.02 (0.11)	0.06 (0.12)	**0.48 (0.1)**	0.06 (0.12)	0.02 (0.04)	-0.01 (0.1)	0.05 (0.13)
Number of observations	3,311	3,311	3,311	3,311	3,311	3,311	3,065	3,352
-2LogLikelihood	511.9	526.9	494.7	495.6	511.9	1220.3	-624.5	3287.2
Akaike' Information Criterion	601.9	614.9	584.7	585.6	603.9	1308.3	-534.5	3377.9
Bayesian Information Criterion	703.1	713.9	685.9	673.4	707.4	1576.9	-438.8	3479.1
Variance of error terms	0.23	0.24	0.23	0.23	0.23	0.31	0.17	0.54
Variance of random effect								
Study effect	0.07	0.06	0.07	-	0.03	-	0.04	0.07
Author effect	-	-	-	0.12	0.03	-		

Note: standard errors are in parentheses, parameter estimates significant at 5% are reported in bold – Model (1): "baseline" – Model (2): no correction for publication bias – Model (3): DF used to weight observations – Model (4): Random author effect – Model (5): Random author effect – Model (6): Fixed effect MRA – Model (7): Treatment of outliers by trimming method – Model (8): No treatment of outliers

Source: author`s calculations

Fourth, turning to the characteristics related to the specification of the model and method used to estimate demand elasticities, the main effect on estimated elasticity values observed appears to be related to the model used to represent demand. Price elasticity estimates derived from flexible forms, such as the AIDS of quadratic or linear form and from Rotterdam and Translog demand systems, appear significantly higher than those derived from the LES and CES and lower than those derived from ad hoc single equations. This result stands in contrast with the conclusions of CORNELSEN et al. (2016), who find no significant effects of the functional form used to estimate food demand price elasticities. However, these authors only distinguish AIDS and "non-AIDS" forms of demand systems. On the other hand, they find estimation methods to have a significant impact on estimated elasticities, which is not found to be the case in our study for the same classification of estimation methods. Their result might in fact be related to effects of the functional form used to estimate elasticities, as the selection of an estimation method generally results from the specification of the econometric model to be estimated. Functional forms appear to have less impact on estimated income elasticities with only the Translog demand system having an impact on these elasticities that is significantly different from other functional forms. However, while adopting a multi-stage budgeting framework is found to have no significant impact on price elasticity estimates, it appears to lead to significantly lower income elasticities, and this is the case, although we only consider unconditional income elasticities. This shows that methodological strategies influence the value of estimated elasticities and calls for sensitivity analyses from economists using estimated elasticities in their models.

All conclusions regarding the effects of income, products, regions, functional forms and multi-stage budgeting remain valid when we consider different MRA model specifications (Models (2)-(6)) or sample selection methods (Models (7)-(8)). According to the Aikaike and Bayesian Information Criteria (AIC and BIC) reported at the end of Tables 5 and 6, the specification including a correction of publication bias (Model (1)) is preferred to the specification without this correction (Model (2)), which was expected. Furthermore, among the different specifications used to account for unobserved heterogeneity and potential correlations between elasticity estimates (random study effects in Model (1), random author effects in Model (4), both types of effects in Model (5) and no effect in Model (6)) [8], the model including random study effects appears to be the preferred one. Most of the differences in estimation results actually appear with the fixed effect-size MRA model (Model (6)), where several explanatory variables that are found, in Model (1), to have no significant impact on elasticity estimates, such as the decade a dataset refers to, the type of data concerned, the levels of product aggregation or the distinctions between urban and rural households, appear to be significant in Model (6). As is shown by BATEMAN and JONES (2003), not accounting for the heterogeneity between studies that remains after observable study characteristics are taken into account can lead to misleading conclusions regarding the impacts of several of these characteristics on price and income elasticity estimates.

5 Conclusion

The main purposes of this paper were twofold: first, to reveal general patterns characterizing the demand elasticities of food products and second, to identify the major sources of heterogeneity between the estimates of the elasticities available in the literature to help economists to select empirical estimates of these key parameters for their simulation models. To achieve these objectives, we conducted a broad literature review of food demand elasticity estimates and performed an MRA. The MRA applied herein differs from those of previous works addressing similar issues in several respects. First, we considered not only price but also income elasticity, which can have considerable impacts on the outcomes of simulation models. Second, relative to previous studies, additional variables characterizing elasticity estimates were included in our analysis. We notably considered more detailed categorizations of functional forms representing food demand and information on household income levels. Third, in line with the MAER-NET protocol, heteroscedasticity issues were accounted for and publication selection bias was addressed, and we relied on a mixed-effect MRA model to account for potential correlations between elasticity estimates collected from the same study.

[8] Models (3), (6), (7) and (8) are not directly comparable to the other specifications since they are not estimated based on the same data. In Model (3), a different variable is used to weight observations, and Model (7) and (8) are estimated based on different samples of observations.

Our results first reveal some general patterns regarding the levels of price and income elasticities of food demand elasticities. We found demand to be less responsive to income and price changes for staple products, which conforms to economic theory. It also appears that income levels have important impacts on income and price elasticities both at country (GDP) and household levels: the higher the income is, the lower the level of elasticity. We also found demand elasticities to present different patterns depending on the global region considered apart from any income level considerations.

Beyond these factual elements and perhaps more importantly, the functional forms used to represent food demand were found to significantly affect price elasticity estimates, and the adoption of multi-stage budgeting frameworks was found to significantly impact unconditional income elasticity estimates. These results contrast with those obtained through previous meta-analysis and can notably be attributed to the more thorough representation of the modelling food demand considered here. Our results show that methodological strategies influence the value of estimated elasticities and call for sensitivity analyses from economists using estimated food demand elasticities to calibrate their models. This is all the more important because food demand elasticities are crucial parameters in the calibration of simulation models used to assess the impacts of agricultural policy reforms.

Sensitivity analyses were performed to test the robustness of our results to the specifications of the MRA models. Our main results proved to be robust to the assumptions underlying these models.

Finally, it should be noted that the meta-analysis presented here does not consider potential differences in food elasticities between domestic and imported goods. This is because the primary studies included in our dataset do not provide sufficient information for analysing this issue, as none of them distinguish between imported and domestic goods. This is, however, an important question since, as shown by SEALE et al. (2003b), for example, in the case of wine in the US, income and price elasticities can significantly differ between domestic and imported goods and between different sources of imported goods. Notably, this can have important implications when using elasticities to calibrate models aimed at simulating the impacts of trade policies. This point should be considered in future work analysing food demand elasticity estimates.

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Acknowledgements

This work has been partly financed by the International Food Policy Research Institute (IFPRI).

The author is grateful to David Laborde for his advises on the preliminary steps of this work, to Laure Latruffe and two anonymous reviewers for their helpful comments on the paper and to Christine Mesquida for her careful review of the references included in the meta-analysis.

FABIENNE FEMENIA, PHD
SMAART-LERECO 1302 SMART
4 Allée Adolphe Bobierre, 35011 Rennes, France
e-mail: fabienne.femenia@inra.fr