A meta-analysis of the price and income elasticities of food demand

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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.

Keywords: elasticities, estimation, food demand, meta-analysis

JEL classification: Q11, Q18, D12, C13

Une méta-analyse des élasticités prix et revenu de la demande de biens alimentaires

Résumé

Les élasticités prix et revenu de la demande de biens alimentaires sont des paramètres cruciaux intervenant dans le calibrage des modèles de simulation qui sont utilisés pour évaluer l'impact de réformes politiques ou faire des projections de long terme, notamment en ce qui concerne dans les secteurs agricoles. De nombreuses valeurs estimées de ces paramètres sont aujourd'hui disponibles dans la littérature économique. Nos principaux objectifs ici sont, d'une part, de mettre en avant des éléments caractérisant de manière générale ces élasticités prix et revenu et, d'autre part, d'identifier les principales sources de variabilité de leurs valeurs estimées dans la littérature. Pour répondre à ce double objectif nous collectons dans la littérature un large ensemble d'élasticités estimées de demande de biens alimentaires que nous analysons ensuite à l'aide d'une méta-régression.

Nos résultats mettent en évidence un impact important du niveau de revenu, à la fois au niveau pays (produit intérieur brut-PIB) et au niveau ménage, sur les élasticités prix et revenu : plus le revenu est élevé, moins la demande de biens alimentaires est élastique. Il apparait également que les réponses de la demande aux variations de revenu et de prix diffèrent entre régions du monde indépendamment des différences de revenus pouvant exister entre ces régions. D'un point de vue méthodologique, nous trouvons que le choix de la forme fonctionnelle utilisée pour représenter la demande a un effet significatif sur les élasticités estimées. Ce résultat souligne l'importance de la spécification des fonctions de demande, en particulier de leur flexibilité, dans les modèles de simulation.

Mots-clés : élasticités, estimation, demande de biens alimentaires, méta-analyse

Classification JEL : Q11, Q18, D12, C13

A meta-analysis of the price and income elasticities of food demand

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 next section is devoted to the description of the database of food demand elasticity estimates that we build to fulfil our objectives. In the third 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 fouth section, and conclusions are drawn in the last section.

2. Data search and coding methods

In line with the MAER-NET protocol, we provide here a detailed description of how the literature was searched and coded to build our database of price and income elasticity estimates. The procedure used to collect the references included in the database is presented first. A second part is devoted to the coding of information collected from primary studies. Finally, the selection of the sample used in the meta-analysis is described in a third part.

2.1 Data collection

Diverse data sources are commonly used to calibrate demand functions in global economic models (see, for instance, Valin *et al.* (2014) for a summary of data sources used in ten computable general equilibrium and partial equilibrium models). Several models, such as GCAM (Clarke *et al.*, 2007), GLOBIOM (Havlik *et al.*, 2011) and 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 Muhammad *et al.* (2011)[1]) to calibrate their demand function parameters. In these reports, price and income elasticities are estimated for eight broad food categories (beverages and tobacco, bread and cereals, meat, fish, dairy products, oils and fats, fruits and vegetables and other food products) and for a large number of countries; own price and income elasticities are estimated for 114 countries in Seale *et al.* (2003a) and for 144 countries in Muhammad *et al.* (2011). This broad level of country coverage renders these elasticity data well-suited for calibrating large simulation models. Economists might however wish to use other source of elasticities for different reasons when, for instance, they consider food products at a higher disaggregation level or when they wish to

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[1] Muhammad *et al.* (2011) is an updated version of Seale *et al.* (2003a) considering more recent data and more countries.

compare results obtained with a calibration of demand parameters based on USDA estimates to those obtained with a calibration based on other estimates given 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. This represents a total of 1,800 estimates of own price and income elasticities collected from 72 papers. While the database covers a large variety of products at various aggregation levels[2], few countries are included. The US is well-represented, with 1,166 elasticity estimates collected from 44 papers, which is not surprising given the focus of the database on papers published or presented in this country. The other elasticities are essentially for China with 528 estimates collected from 22 papers, and only four other countries (Canada, Indonesia, Portugal and Saudi Arabia) are represented, with a few estimates collected from up to three papers.

These two data sources, namely, the USDA's estimates given in Seale *et al.* (2003a) and Muhammad *et al.* (2011) and the USDA's literature review database, were used to build the database employed to conduct the meta-analysis presented here. More precisely, we started with the structure of the USDA literature review database, which already includes useful information on each elasticity estimate, such as the references of the papers from which the estimates have been collected; the countries, products and time periods concerned; the types of data used to conduct estimations; and the demand models estimated. The elasticities estimated by Seale *et al.* (2003a) (1,824 estimates) and Muhammad *et al.* (2011) (2,304 estimates) were also included. We then reviewed the primary studies to check the information included in the USDA database and to ensure the consistency of the data. Of the 74 references present in these data, five PhD dissertations were not available to us, thus restricting our ability to verify the data and to collect new information, and we decided to exclude these references.

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 dealing with countries other than the US and China and with a focus on post-2005 studies regardless of country.

The search was performed with Google Scholar in March 2015 using the following combinations of keywords: "price, elasticities, food, demand" and "income, elasticities, food,

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[2] Product aggregation levels vary from global food aggregate (e.g., Han *et al.*, 1997) to very detailed levels (e.g., milk differentiated by fat level (Gould, 1996) or pasta sauces differentiated by brand (Seo and Capps, 1997)).

demand". We did not limit our search to published papers; working papers, reports, and papers presented at conferences were also included. A total of 72 references were collected in this way. All price and income elasticity estimates of food demand reported in these references were collected. Among own price elasticities we distinguished uncompensated (Marshallian) price elasticities from compensated (Hicksian) elasticities. This distinction is important since both elasticities do not measure the same type of demand response to prices: uncompensated elasticities measure the impact of a change in the price of one good by holding income and the prices of other goods constant, and they thus incorporate both income (when the price of one good increases, the income available to consume other goods decreases) and substitution effects (when the price of one good increases, other goods become relatively less expensive); compensated elasticities measure the impacts of a change in the price of one good holding consumer 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. The two types of price elasticities can thus not be considered equivalent or be studied simultaneously. Given the small number of compensated own price elasticity estimates present in the USDA literature review database and reported in the references that we collected (680 of 5,968 own price elasticity estimates), 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), are designed to provide estimates of food demand elasticities for subsequent use to understand the structure of demand for food products or to simulate the evolution of such demand under various scenarios. While Seale *et al.* (2003a) and Muhammad *et al.* (2011) include a large number of countries, most of these papers focus on one particular country and provide estimates for a complete set of food products or for one particular food sector, such as meat, dairy products or fruits and vegetables. 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 focused 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 for illustrative purposes to assess the proposed approach.

2.2 Information included and data coding

Based on the information collected during the review process, our database includes several variables in addition to the values of elasticity estimates and the references of the primary studies from which they have been collected[3].

A first set of information included in our database relates to the primary data that have been used to estimate the demand elasticities. Information relates to the type of data used (time series, panel or cross section), to whether they have been collected at the micro (household) or macro (country) level, to the decade in which they have been collected, which ranges from 1950 to 2010, and to the countries and products to which these data refer. To homogenize the information on food products, product names as they appear in the primary studies are mapped to the following eight product categories: beverages and tobacco, cereals, dairy products, fruits and vegetables, oils and fats, meat and fish, other food products and non-food products. Given that 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. The following four aggregation levels are considered: "global food aggregate"; "product category aggregate", which corresponds to the aforementioned categories; "product level", which refers to single products, for instance bananas and apples for fruits, beef and poultry for meat, wheat and corn for cereals, etc.; "differentiated product level", which refers to products differentiated by specific characteristics, for instance, organic or conventional for fruits and vegetables or cereals and types of cut for meat. Our mapping of product names, product categories and aggregation levels is presented in Appendix 2. Country names are converted into standard ISO-alpha-3 country codes (International Organization for Standardization) and are mapped to 11 world regions according to the classification provided in Appendix 3. Where applicable, we also report in our data information concerning the types (urban, rural or any type) and levels of income of households from which the primary data have been collected. While we also could have considered simple averages of elasticities for primary studies reporting estimates for different household categories, as in Cornelsen *et al.* (2015), this would have led to a loss of potentially important information. The levels of household income are homogenized across studies by reporting these levels as a percentage of the highest income considered in the study rather than as nominal income amounts.

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[3] Available human and financial resources did not allow for the data to be checked by an independent reviewer as recommended under the MAER-NET protocol. An additional check was however performed by the author herself to limit potential data coding errors.

The second type of information included in the database relates to the precision of the elasticity estimates. This information is indeed necessary for assessing an important issue of meta-analysis, which is publication selection bias. Stanley (2005) identifies three sources of publication bias as follows: (i) papers are more likely to be accepted for publication when they conform to conventional views; (ii) when different models and/or estimation methods are tested, authors are more likely to report results corresponding to conventional views; and (iii) statistically significant results are treated more favourably. Hence, authors, reviewers and journal editors may have a preference for statistically significant results in line with conventional views, which results in studies finding small or insignificant estimates or estimates with unexpected signs to remain unpublished. In our case, publication bias may lead 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 a publication selection bias in our data. This can be accomplished by relying on a method proposed by Egger *et al.* (1997), the PET test (precision effect test), which involves regressing effect size estimates (demand elasticity estimates in our case) on an inverse indicator of their precision. This method allows one to test both for the presence of a publication bias and for the existence of a "true" effect size. Egger *et al.* (1997) suggest using the inverse standard errors of effect size estimates as indicators of their precision and thus regressing effect sizes on standard errors of estimates. When publication bias is detected, it must be accounted for in the subsequent meta-regression analysis. Stanley and Doucouliagos (2014) recommend that the PEESE (precision effect estimate with standard error) estimator be used in such cases, i.e., including the variances of effect size estimates as explanatory variables in the meta-regression. This approach thus also involves collecting information on the standard errors corresponding to each effect size (demand elasticities in our case) estimates from the primary studies. Unfortunately, we face here the same issue as that faced by other meta-analyses of demand elasticities: while studies generally report standard errors of primary estimates (estimates of demand model parameters), few report these elements for the elasticities that are computed from these estimates. In our sample, less than 30% of estimated elasticities have associated standard error estimates and/or Student's t-test statistics, and we do not generally have sufficient information (complete covariance matrix of estimates) to use delta methods to compute standard error elasticity estimates. One solution involves only selecting studies with standard errors. This approach was adopted by Ogundari and Abdulai (2013) in their study of calorie-income elasticities and by Fogarty (2010) in his paper on alcohol demand elasticities. However, in our case, this would have substantially reduced the sample size and thus limited the possibility of conducting an

MRA. Some authors (Green *et al.*, 2013; Cornelsen *et al.*, 2015) do not treat publication bias because of this lack of standard error data. To avoid this issue we use inverse sample sizes or degrees of freedom (DF) instead of standard errors. Day (1999), among others, indeed demonstrates the link between sample sizes and standard deviations of estimates, and Egger *et al.* (1997) recommend the use of sample size or DF as a measure of precision in the absence of standard error estimates. These two pieces of information are thus collected and added to our database.

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

2.3 Sample selection

This subsection presents the selection procedure applied to the data sample used for the meta-analysis.

A first round of data selection was conducted based on the aggregation level of food products considered in the data used in the primary studies. Two of the four product aggregation levels identified in our dataset were excluded from the analysis as follows: the "global food aggregate" level and the "differentiated product" level, which includes very specific products that are of little relevance for large simulation models and for which elasticity estimates tend to be extremely high in absolute terms. This selection approach led to us exclude 42 primary studies and 1,959 elasticity estimates.

Then, we excluded primary studies that did not provide the number of observations used to estimate the elasticities since, as previously mentioned, this information is used as a proxy for the precision of elasticity estimates in the MRA. This selection approach led us to exclude 5 primary studies and 372 elasticity estimates.

We do not consider in our analysis the "non-food" and "beverage and tobacco" product categories, which correspond to 809 elasticity estimates. The "non-food" category indeed falls outside of the scope of our study and the demand for "beverage and tobacco" exhibits very specific patterns, which explains why a large number of meta-analyses have already been conducted on these products specifically.

Finally, as in Cornelsen *et al.* (2015), we consider as outliers price and income elasticities ranging outside of three standard deviations of their respective averages and exclude such outliers from our sample. This represents 63 observations for price elasticities and 41 observations for income elasticities.

The sample of elasticity estimates considered the paper thus includes 6,645 observations collected from 93 primary studies, among which 3,334 are price elasticities and 3,311 are income elasticities.

2. 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.

2.1 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.

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.

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 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.

2.2 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.

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. Elasticities - summary statistics by world regions

		Own price elasticities						Income elasticities					
		Cereals	Dairy	Fruit and veg.	Meat	Oils and Fat	Other food	Cereals	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

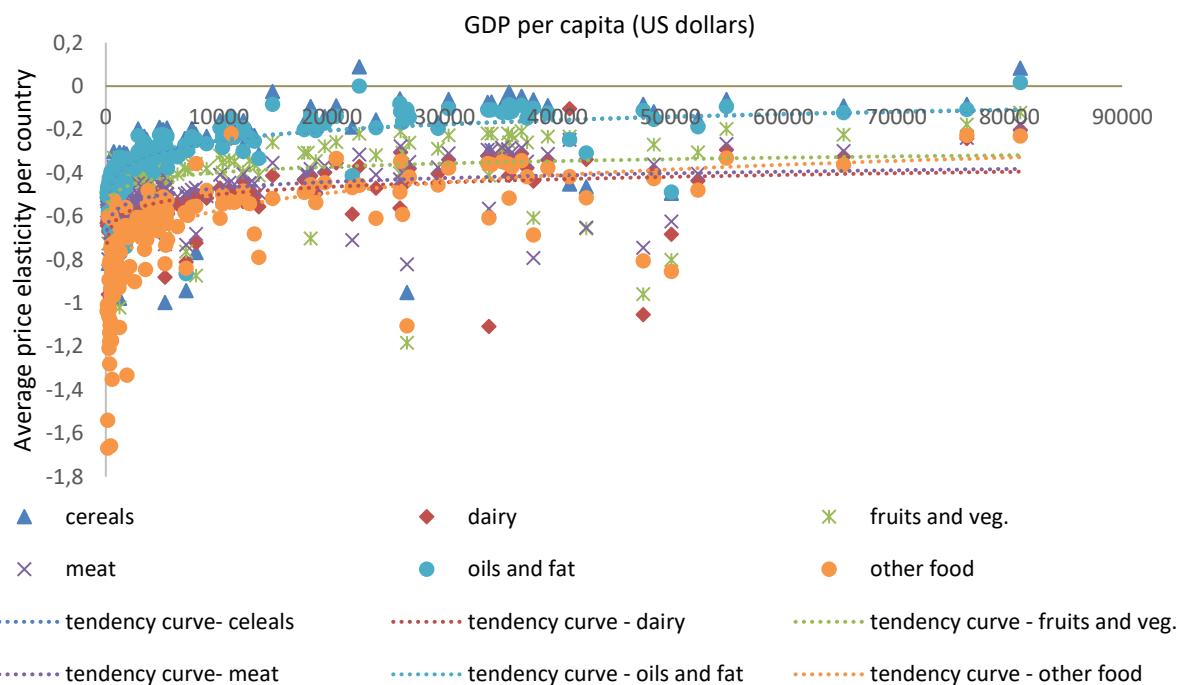|		Own price elasticities						Income elasticities					
		Cereals	Dairy	Fruit and veg.	Meat	Oils and Fat	Other food	Cereals	Dairy	Fruit and veg.	Meat	Oils and Fat	Other food
Former Soviet Union	Weighted average	-0.32	-0.59	-0.43	-0.55	-0.34	-0.68	0.42	0.77	0.56	0.71	0.44	0.89
	Weighted S.D.	0.16	0.14	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.

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
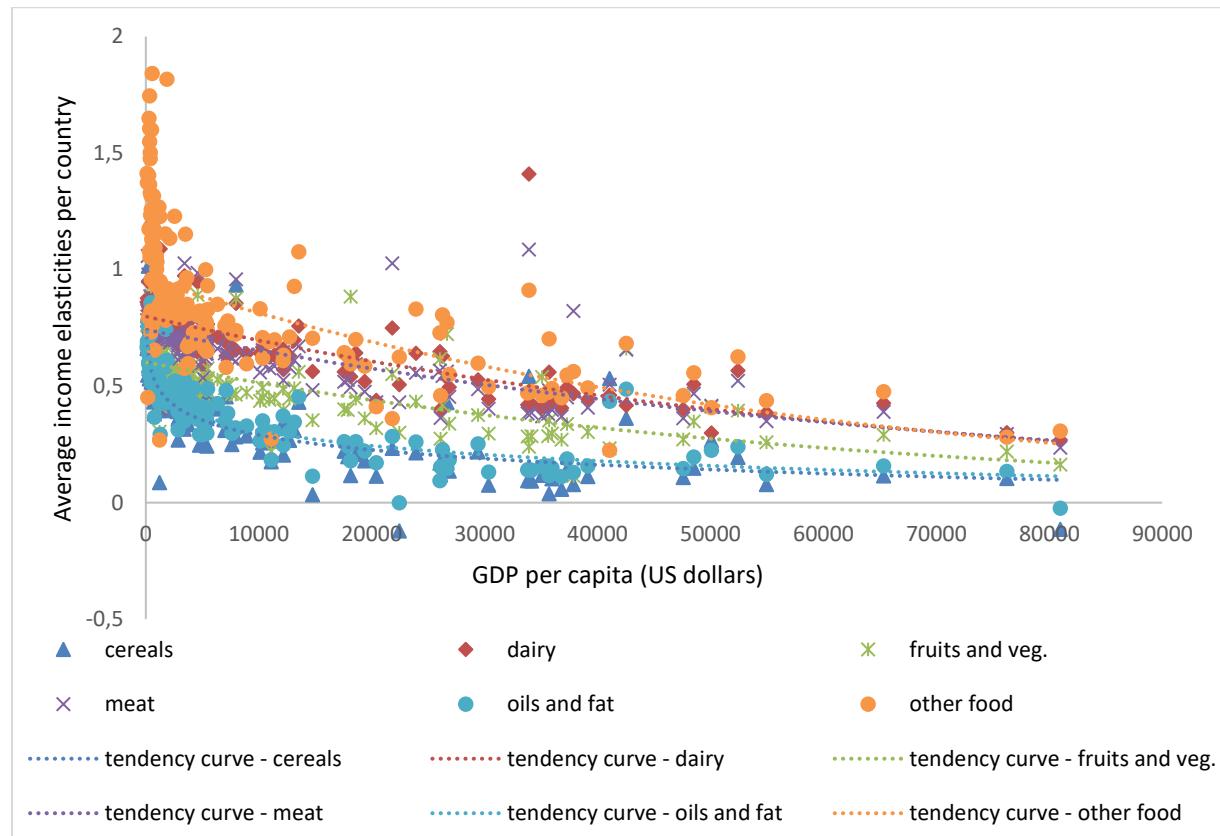
Figure 2. Evolution of price elasticities with GDP per capita

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 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.

Figure 3: Evolution of income elasticities with households' income
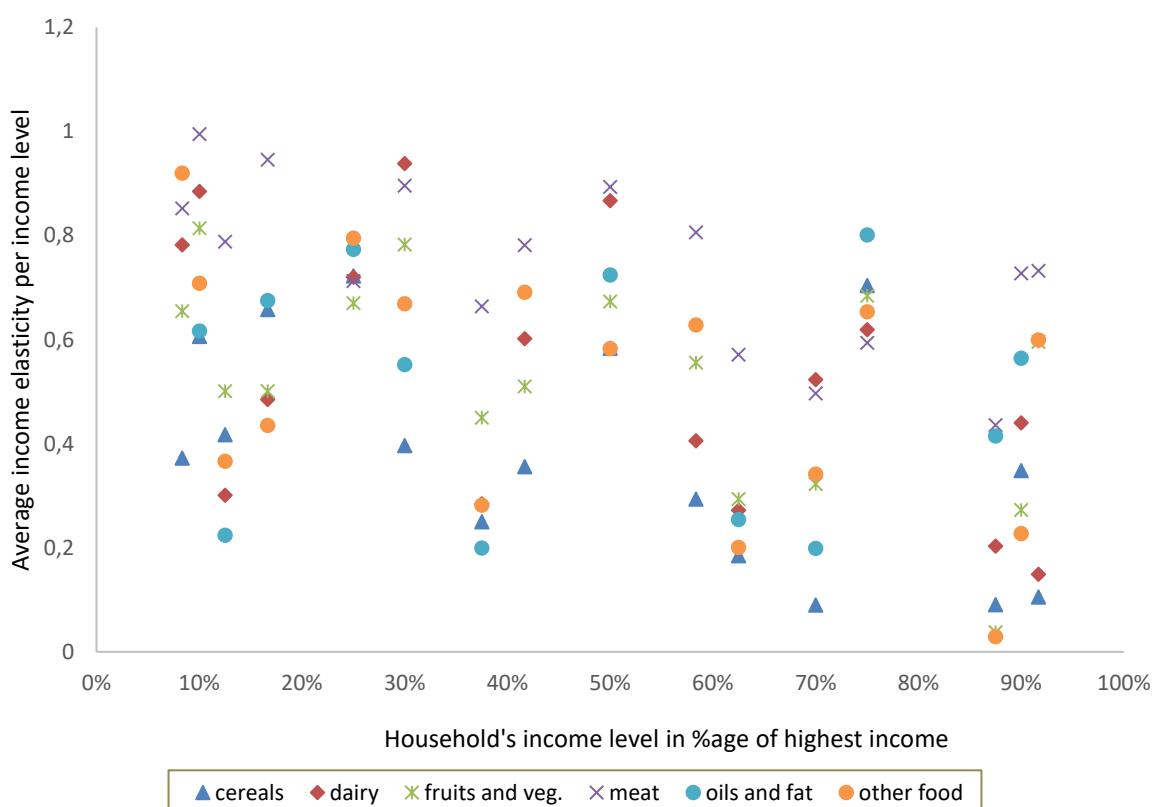
Figure 4: Evolution of price elasticities with households' income
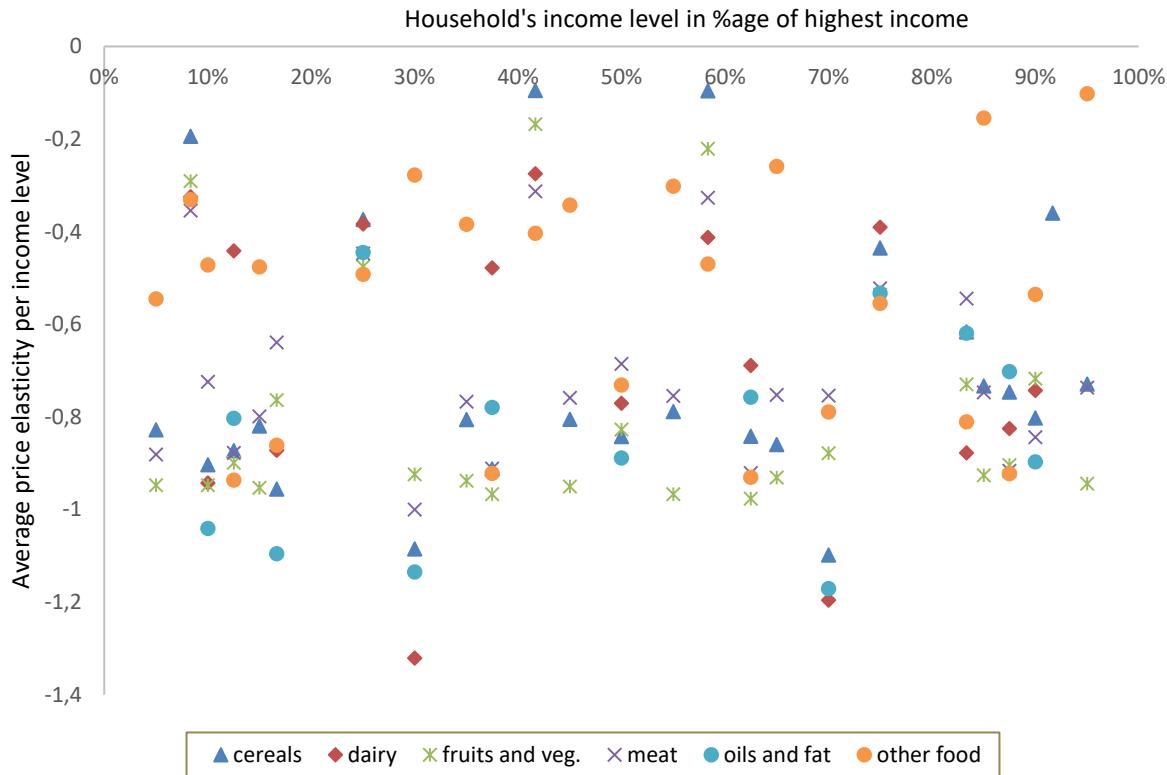
3. **Methodological sources of heterogeneity in elasticity estimates**

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 semi-definiteness of the Slutsky matrix. These restrictions can, however, be imposed in econometric estimations (see, e.g., Moschini (1998 and 1999) and Ryan and Wales (1998)).

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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.

Finally, should be noted that 11% of the primary studies use other specific models to obtain demand elasticities[6].

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

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[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. (2004). 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.

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 2.2, 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, p. 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

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[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.

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.

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.

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**	**-0.78**	**0.73**	**0.73**
	(0.004)	**(0.01)**	**(0.01)**	**(0.01)**
Inverse square root of primary sample size (*test for publication bias*)	**7.80**	-	**-4.75**	-
	(1.23)		**(1.35)**	
Inverse square root of degrees of freedom (*test for publication bias*)	-	**7.67**		**-4.67**
		(1.23)		**(1.34)**
N	3334	3334	3311	3311
R²	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

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 3 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.

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
<u>Time series</u>	-0.66	401	0.69	331
Data level				
Individual	-0.70	1154	0.70	1153
<u>Country</u>	-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
<u>Cereals</u>	-0.52	520	0.45	509
Product aggregation level				
Product level	-0.68	1263	0.69	1253
<u>Aggregate level</u>	-0.49	2071	0.60	2058

	Own price elasticities		Income elasticities	
	Average elasticity	Nb Obs	Average elasticity	Nb Obs
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
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

	Own price elasticities		Income elasticities	
	Average elasticity	Nb Obs	Average elasticity	Nb Obs
Prices adjusted for quality				
Yes	-0.62	165	0.80	200
<u>No</u>	-0.57	3191	0.62	3111
Individuals' characteristics included				
Yes	-0.57	2933	0.62	2735
<u>No</u>	-0.64	401	0.71	576

	Own price elasticities		Income elasticities	
	Average elasticity	Nb Obs	Average elasticity	Nb Obs
Products' characteristics included				
Yes	-0.58	24	0.99	16
<u>No</u>	-0.57	3310	0.64	3295
Time variables included				
Yes	-0.84	308	0.71	344
<u>No</u>	-0.55	3026	0.63	2967
Multi-stage budgeting				
Yes	-0.55	2356	0.58	2082
<u>No</u>	-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

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 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.

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	**-0.36**	-0.25	-0.16	-0.25	**-0.33**	-0.02	-0.32
	(0.15)	**(0.15)**	(0.15)	(0.17)	(0.15)	**(0.06)**	(0.15)	(0.18)
Publication bias correction term	**-14.95**		**-15.20**	**-14.87**	**-14.96**	-1.21	**-49.93**	-8.57
	(5.73)		**(5.76)**	**(5.82)**	**(5.73)**	(2.52)	**(11.23)**	(6.86)
Publication date trend (1976=1)	-0.004	-0.004	-0.004	-0.002	-0.004	-0.003	-0.010	-0.010
	(0.005)	(0.005)	(0.01)	(0.003)	(0.005)	(0.001)	(0.005)	(0.01)
Data decade trend (1950's=1)	0.03	0.03	0.03	0.03	0.03	**0.04**	0.002	0.04
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	**(0.01)**	(0.03)	(0.03)

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)
GDP per capita (in 1,000 US$)	**0.005** **(0.0005)**	**0.005** **(0.000)**	**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)**

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)
Latin America	**-0.08**	-0.07	**-0.08**	**-0.07**	**-0.08**	**-0.15**	**-0.07**	-0.07
	(0.04)	(0.04)	**(0.04)**	**(0.04)**	**(0.04)**	**(0.03)**	**(0.03)**	(0.05)
Middle East	**-0.09**	**-0.09**	**-0.10**	**-0.09**	**-0.09**	**-0.22**	**-0.09**	**-0.10**
	(0.04)	**(0.04)**	**(0.04)**	**(0.04)**	**(0.04)**	**(0.03)**	**(0.03)**	**(0.05)**
North Africa	-0.10	-0.09	-0.10	-0.10	-0.10	**-0.19**	-0.09	-0.10
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	**(0.05)**	(0.05)	(0.07)
Sub-Saharan Africa	**-0.19**	**-0.18**	**-0.19**	**-0.18**	**-0.19**	**-0.28**	**-0.17**	**-0.20**
	(0.04)	**(0.04)**	**(0.04)**	**(0.04)**	**(0.04)**	**(0.03)**	**(0.03)**	**(0.05)**
Oceania	-0.04	-0.03	-0.04	-0.03	-0.04	**-0.10**	-0.04	-0.03
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	**(0.05)**	(0.04)	(0.07)
Urban _vs_ rural households								
Urban	0.03	0.03	0.03	0.03	0.03	**0.09**	0.05	0.03
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	**(0.02)**	(0.03)	(0.04)
Rural	-0.02	-0.02	-0.02	-0.01	-0.02	**0.05**	0.01	-0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	**(0.02)**	(0.03)	(0.04)
Demand model								
AIDS	**-0.39**	**-0.36**	**-0.39**	**-0.60**	**-0.39**	**-0.50**	**-0.32**	**-0.41**
	(0.13)	**(0.13)**	**(0.13)**	**(0.15)**	**(0.13)**	**(0.04)**	**(0.12)**	**(0.15)**
LAIDS	**-0.43**	**-0.40**	**-0.43**	**-0.67**	**-0.43**	**-0.40**	**-0.3**	**-0.44**
	(0.13)	**(0.13)**	**(0.13)**	**(0.15)**	**(0.13)**	**(0.04)**	**(0.11)**	**(0.15)**
QUAIDS	**-0.41**	**-0.39**	**-0.41**	**-0.44**	**-0.41**	**-0.44**	**-0.33**	**-0.44**
	(0.13)	**(0.13)**	**(0.14)**	**(0.15)**	**(0.14)**	**(0.04)**	**(0.12)**	**(0.16)**
Rotterdam	**-0.38**	**-0.34**	**-0.38**	**-0.61**	**-0.38**	**-0.17**	-0.22	-0.33
	(0.15)	**(0.15)**	**(0.15)**	**(0.16)**	**(0.15)**	**(0.07)**	(0.14)	(0.18)
Translog	**-0.36**	**-0.43**	**-0.35**	**-0.61**	**-0.36**	**-0.40**	-0.23	**-0.36**
	(0.16)	**(0.15)**	**(0.16)**	**(0.17)**	**(0.16)**	**(0.05)**	(0.15)	**(0.18)**
Single equation	**-0.55**	**-0.60**	**-0.56**	**-0.60**	**-0.55**	**-0.68**	**-0.96**	**-0.7**
	(0.17)	**(0.17)**	**(0.17)**	**(0.20)**	**(0.17)**	**(0.05)**	**(0.17)**	**(0.19)**
Other	**-0.32**	**-0.30**	**-0.33**	**-0.56**	**-0.33**	**-0.21**	**-0.35**	-0.27
	(0.13)	**(0.13)**	**(0.13)**	**(0.15)**	**(0.13)**	**(0.04)**	**(0.12)**	(0.15)
Zero demands accounted for								
Yes	0.004	0.02	0.004	0.04	0.004	-0.01	-0.03	-0.04
	(0.07)	(0.07)	(0.07)	(0.05)	(0.07)	(0.02)	(0.06)	(0.08)
Prices adjusted for quality								
Yes	-0.07	-0.07	-0.07	**-0.22**	-0.07	0.01	-0.09	-0.04
	(0.06)	(0.06)	(0.06)	**(0.05)**	(0.06)	(0.03)	(0.05)	(0.08)
Individuals' characteristics included								
Yes	-0.15	-0.11	-0.15	-0.02	-0.15	-0.06	**-0.17**	-0.04
	(0.08)	(0.08)	(0.08)	(0.05)	(0.08)	(0.03)	**(0.07)**	(0.1)

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)
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.

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	0.23	0.40	0.35	0.41	**0.74**	0.13	**0.56**
	(0.25)	(0.23)	(0.25)	(0.28)	(0.25)	**(0.08)**	(0.20)	**(0.27)**
Publication bias correction term	**-24.66**		**-23.78**	**-31.76**	**-24.66**	-4.67	10.16	**-17.73**
	(6.29)		**(6.36)**	**(6.48)**	**(6.29)**	(3.37)	(8.14)	**(8.26)**
Publication date trend (1976=1)	0.003	0.01	0.003	0.01	0.003	-0.001	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.004)	(0.01)	(0.002)	(0.01)	(0.01)
Data decade trend (1950's=1)	0.01	**0.01**	0.01	-0.03	0.01	**0.05**	-0.02	-0.04
	(0.03)	**(0.03)**	(0.03)	(0.03)	(0.03)	**(0.02)**	(0.03)	(0.04)
GDP per capita (in 1,000 US$)	**-0.01**	**-0.01**	**-0.01**	**-0.01**	**-0.01**	**-0.01**	**-0.01**	**-0.01**
	(0.0005)	**(0.0005)**	**(0.0005)**	**(0.0005)**	**(0.0005)**	**(0.0005)**	**(0.0005)**	**(0.0005)**
Household income level (%age of highest income)	**-0.19**	-0.21	**-0.19**	**-0.18**	**-0.19**	**-0.21**	**-0.11**	**-0.23**
	(0.03)	(0.03)	**(0.03)**	**(0.03)**	**(0.03)**	**(0.03)**	**(0.03)**	**(0.04)**
Nominal variables								
Type of data								
Panel	-0.25	-0.27	-0.25	0.10	-0.25	**-0.52**	-0.19	-0.26
	(0.25)	(0.24)	(0.25)	(0.21)	(0.25)	**(0.08)**	(0.21)	(0.28)
Cross section	-0.10	-0.11	-0.10	0.29	-0.10	-0.08	-0.12	-0.06
	(0.21)	(0.21)	(0.21)	(0.20)	(0.21)	(0.07)	(0.17)	(0.24)
Data level								
Individual	-0.19	-0.07	-0.18	-0.26	-0.19	0.05	-0.06	-0.11
	(0.18)	(0.17)	(0.18)	(0.19)	(0.18)	(0.06)	(0.15)	(0.21)
Product								
Dairy	**0.29**	**0.29**	**0.28**	**0.28**	**0.29**	**0.28**	**0.26**	**0.34**
	(0.02)	**(0.02)**	**(0.02)**	**(0.02)**	**(0.02)**	**(0.02)**	**(0.01)**	**(0.03)**
Fruits and vegetables	**0.15**	**0.15**	**0.15**	**0.15**	**0.15**	**0.14**	**0.14**	**0.19**
	(0.02)	**(0.02)**	**(0.01)**	**(0.02)**	**(0.02)**	**(0.02)**	**(0.01)**	**(0.02)**
Meat and fish	**0.28**	**0.28**	**0.28**	**0.27**	**0.28**	**0.29**	**0.25**	**0.32**
	(0.01)	**(0.01)**	**(0.01)**	**(0.01)**	**(0.01)**	**(0.02)**	**(0.01)**	**(0.02)**
Oils and fats	**0.05**	**0.05**	**0.05**	**0.05**	**0.05**	**0.05**	**0.03**	**0.11**
	(0.02)	**(0.02)**	**(0.02)**	**(0.02)**	**(0.02)**	**(0.02)**	**(0.02)**	**(0.03)**
Other food products	**0.36**	0.36	**0.36**	**0.36**	**0.36**	**0.34**	**0.33**	**0.44**
	(0.02)	(0.02)	**(0.02)**	**(0.02)**	**(0.02)**	**(0.02)**	**(0.01)**	**(0.02)**
Product aggregation level								
Product level	0.07	0.05	0.07	0.11	0.07	**-0.06**	**0.18**	-0.01
	(0.06)	(0.06)	(0.06)	(0.05)	(0.06)	**(0.03)**	**(0.05)**	(0.07)

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)
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)
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)

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)
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

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)
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.

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.

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,

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[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.

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.

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.

References

Alderman, H. (1986). *The effect of food price and income changes on the acquisition of food by low-income households*. International Food Policy Research Institute, 100 p.

Andreyeva, T., Long, M.W., Brownell, K.D. (2010). The impact of food prices on consumption: a systematic review of research on the price elasticity of demand for food. *American Journal of Public Health*, 100(2): 216-222.

Banks, J., Blundell, R., Lewbel, A. (1997). Quadratic Engel curves and consumer demand. *Review of Economics and Statistics*, 79(4): 527-539.

Barten, A.P. (1964). Consumer demand functions under conditions of almost additive preferences. *Econometrica: Journal of the Econometric Society*, 32(1-2): 1-38.

Bateman, I.J., Jones, A.P. (2003). Contrasting conventional with multi-level modeling approaches to meta-analysis: expectation consistency in UK woodland recreation values. *Land Economics*, 79(2): 235-258.

Borenstein, M., Hedges, L.V., Higgins, J., Rothstein, H.R. (2010). A basic introduction to Fixed-effect and random-effects models for meta-analysis. *Research Synthesis Methods*, 1(2): 97-111.

Carpentier, A., Gohin, A., Sckokai, P., Thomas, A. (2015). Economic modelling of agricultural production: past advances and new challenges. *Revue d'Études en Agriculture et Environnement*, 96(1): 131-165.

Carpentier, A., Guyomard, H. (2001). Unconditional elasticities in two-stage demand systems: an approximate solution. *American Journal of Agricultural Economics*, 83(1): 222-229.

Chen, D., Abler, D., Zhou, D., Yu, X., Thompson, W. (2016). A meta-analysis of food demand elasticities for China. *Applied Economic Perspectives and Policy*, 38(1): 50-72.

Christensen, L.R., Jorgenson, D.W., Lau, L.J. (1975). Transcendental logarithmic utility functions. *The American Economic Review*, 65(3): 367-383.

Cipollina M., Salvatici, L. (2010). Reciprocal trade agreements in gravity models: a meta-analysis. *Review of International Economics*, 18(1): 63-80.

Clarke, L., Edmonds, J., Jacoby, H., Pitcher, H., Reilly, J., Richels, R. (2007). *Scenarios of greenhouse gas emissions and atmospheric concentrations*. US Department of Energy Publications, 116 p. Available at https://science.energy.gov/~/media/ber/pdf/Sap_2_1a_final_all.pdf.

Clements, K.W., Gao, G. (2015). The Rotterdam demand model half a century on. *Economic Modelling*, 49: 91-103.

Clements, K.W., Wu, Y., Zhang, J. (2006). Comparing international consumption patterns. *Empirical Economics*, 31(1): 1-30.

Cornelsen, L., Green, R., Turner, R., Dangour, A.D., Shankar, B., Mazzocchi, M., Smith, R.D. (2015). What Happens to Patterns of Food Consumption when Food Prices Change? Evidence from A Systematic Review and Meta-Analysis of Food Price Elasticities Globally. *Health Economics*, 24(12): 1548-1559.

Cornelsen, L., Mazzocchi, M., Green, R., Dangour, A.D., Smith, R.D. (2016). Estimating the Relationship between Food Prices and Food Consumption-Methods Matter. *Applied Economic Perspectives and Policy*, 38(3): 546-561.

Day, B. (1999). A meta-analysis of wage-risk estimates of the value of statistical life. *EC, Benefits transfer and the economic valuation of environmental damages*. European Commission, Brussels, 29 p. Available at http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.550.7320&rep=rep1&type=pdf

Deaton, A. (1988). Quality, quantity, and spatial variation of price. *The American Economic Review*, 78(3): 418-430.

Deaton, A., Muellbauer, J. (1980). An almost ideal demand system. *The American economic review*, 70(3): 312-326.

Disdier, A.C., Head, K. (2008). The puzzling persistence of the distance effect on bilateral trade. *The Review of Economics and Statistics*, 90(1): 37-48.

Eales, J.S., Unnevehr, L.J. (1988). Demand for beef and chicken products: separability and structural change. *American Journal of Agricultural Economics*, 70(3): 521-532.

Edgerton, D.L. (1997). Weak separability and the estimation of elasticities in multistage demand systems. *American Journal of Agricultural Economics*, 79(1): 62-79.

Egger, M., Smith, G.D., Schneider, M., Minder, C. (1997). Bias in meta-analysis detected by a simple, graphical test. *Bristish Medical Journal*, 315(7109): 629-634.

Fabiosa, J.F., Jensen, H.H. (2003). *Usefulness of incomplete demand model in censored demand system estimation*. Paper prepared for Presentation at the 2003 Annual meeting, July 27-30, Montreal, Canada, No. 21923. American Agricultural Economics Association (New Name 2008: Agricultural and Applied Economics Association). Canada.

Fang, C., Beghin, J.C. (2002). Urban demand for edible oils and fats in China: Evidence from household survey data. *Journal of Comparative Economics*, 30(4): 732-753.

Fogarty, J. (2010). The demand for beer, wine and spirits: A survey of the literature. *Journal of Economic Surveys*, 24(3): 428-478.

Gallet, C. (2010). The income elasticity of meat: a meta-analysis. *The Australian Journal of Agricultural and Resource Economics*, 54(4): 477-490.

Gallet, C. (2008). Meat meets meta: A quantitative review of the price elasticity of meat. *American Journal of Agricultural Economics,* 92(1): 258-272.

Gould, B.W. (1996): Factors affecting US demand for reduced-fat fluid milk. *Journal of Agricultural and Resource Economics*, 21 (1): 68-81.

Green, R., Cornelsen, L., Dangour, A.D., Turner, R., Shankar, B., Mazzocchi, M., Smith, R.D. (2013). The effect of rising food prices on food consumption: systematic review with meta-regression. *British Medical Journal*, 346: f3703.

Hahn, W.F. (2001). *Maximum likelihood estimation of a random coefficient meat demand system*. Paper prepared for Presentation at the 2001 Summer Meetings of the American Agricultural Economics Association, Chicago, IL, 19 p. Available at https://ageconsearch.umn.edu/record/20573/files/sp01ha02.pdf

Han, T., Cramer, G.L. Wahl, T.I. (1997): *Rural household food consumption in China: evidence from the Rural Household Survey*. Paper prepared for Presentation at the 1997 WAEA Meeting July 13-16, Reno, NY.

Havlík, P., Schneider, U.A., Schmid, E., Böttcher, H., Fritz, S., Skalsky, R., Aoki, K., De Cara, S., Kindermann, G., Kraxner, F., Leduc, S., McCallum, I. Mosnier, A., Sauer, T., Obersteiner, M. (2011). Global land-use implications of first and second generation biofuel targets. *Energy Policy*, 39(10): 5690-5702.

Heien, D., Wessels, C.R. (1990). Demand systems estimation with microdata: a censored regression approach. *Journal of Business and Economic Statistics*, 8(3): 365-371.

Higgins, J.P., Thompson, S.G. (2002). Quantifying heterogeneity in a meta-analysis. *Statistics in Medicine*, 21(11): 1539-1558.

Huang, K.S., Lin, B.H. (2000). *Estimation of food demand and nutrient elasticities from household survey data*. Washington, DC: US Department of Agriculture, Economic

Research Service. Technical Bulletin No. 1887, 24 p. Available at https://core.ac.uk/download/pdf/7083123.pdf

Keller, W.J., Van Driel, J. (1985). Differential consumer demand systems. *European Economic Review*, 27(3): 375-390.

Laborde, D., Valin, H. (2012). Modeling land-use changes in a global CGE: assessing the EU biofuel mandates with the MIRAGE-BioF model. *Climate Change Economics*, 3 (3): 1250017.

Lee, L.F., Pitt, M.M. (1986). Microeconometric demand system with binding nonnegativity constraints: the dual approach. *Econometrica: Journal of the Econometric Society*, 54(5): 1237-1242.

Melo, P.C., Abdul-Salam, Y., Roberts, D., Gilbert, A., Matthews, R., Colen, L., Mary, S., Y Paloma, S.G (2015). *Income elasticities of food demand in Africa: A meta-analysis*. JRC Technical report. European Commission. Sevilla. Spain, 74 p. Available at http://publications.jrc.ec.europa.eu/repository/bitstream/JRC98812/jrc98812_jrc_report_m eta_analysis_final.pdf

Moschini, G. (1999). Imposing local curvature conditions in flexible demand systems. *Journal of Business and Economic Statistics*, 17(4): 487-490.

Moschini, G. (1998). The semiflexible almost ideal demand system. *European Economic Review*, 42(2): 349-364.

Muhammad, A., Seale, J.L., Meade, B., Regmi, A. (2011). *International Evidence on Food Consumption Patterns: An Update Using 2005 International Comparison Program Data.* USDA-ERS Technical Bulletin No. 1929, 59 p. Available at https://core.ac.uk/download/pdf/6718963.pdf

Nelson, J.P. (2013a). Meta-analysis of Alcohol Price and Income Elasticities – With Corrections for Publication Bias. *Health Economics Review*, 3(1): 17.

Nelson, J.P. (2013b). Robust demand elasticities for wine and distilled spirits: Meta-Analysis with corrections for outliers and publication bias. *Journal of Wine Economics*, 8(3): 294-317.

Nelson, J.P., Kennedy, P.E. (2009). The use (and abuse) of meta-analysis in environmental and natural resource economics: an assessment. *Environmental and Resource Economics*, 42(3): 345-377.

Neves, P.D. (1994). A class of differential demand systems. *Economics Letters*, 44(1-2): 83-86.

Ogundari, K., Abdulai, A. (2013). Examining the Heterogeneity in Calorie-income elasticities: A Meta-analysis. *Food Policy*, 40(6): 119-128.

Pinstrup-Andersen, P, Caicedo, E. (1978). The potential impact of changes in income distribution on food demand and human nutrition. *American Journal of Agricultural Economics*, 60(3): 402-415.

Roberts, C.J. (2005). Issues in meta-regression analysis: an overview. *Journal of Economic Surveys*, 19(3): 295-298.

Robinson, S., Mason d'Croz, D., Islam, S., Sulser, T.B., Robertson, R.D., Zhu, T., Gueneau, A., Pitois, G., Rosegrant, M.W. (2015). *The International Model for Policy Analysis of Agricultural Commodities and Trade (IMPACT): Model description for version 3*. IFPRI Discussion Paper 1483. Washington, D.C, 55 p. Available at http://ebrary.ifpri.org/utils/getfile/collection/p15738coll2/id/127162/filename/127373.pdf

Rude, J.I., Meilke, K.D. (2004). Developing policy relevant agrifood models. Journal of *Agricultural and Applied Economics*, 36(2): 369-382.

Ryan, D. L., Wales, T.J. (1998). A simple method for imposing local curvature in some flexible consumer-demand systems. *Journal of Business & Economic Statistics*, 16(3): 331-338.

Sam, A.G., Zheng, Y. (2010). Semiparametric estimation of consumer demand systems with micro data. *American Journal of Agricultural Economic*, 92(1): 246-257.

Santeramo, F.G., Shabnam, N. (2015). The income-elasticity of calories, macro-and micro-nutrients: What is the literature telling us? *Food Research International*, 76(4): 932-937.

Schafgans, M.M.A. (2004). Finite Sample Properties for the Semiparametric Estimation of the Intercept of a Censored Regression Model. *Statistica Neerlandica*, 58(1): 35-56.

Seale, J.L., Regmi, A., Bernstein, J. (2003a). *International evidence on food consumption patterns*. USDA Technical Bulletin No. TB-1904. 70 p. Available at https://ageconsearch.umn.edu/record/33580/files/tb031904.pdf.

Seale, J.L., Marchant, M.A., Basso, A. (2003b). Imports versus domestic production: A demand system analysis of the US red wine market. *Review of Agricultural Economi*cs, 25(1): 187-202.

Selvanathan, S., Selvanathan, E.A. (1993). A cross-country analysis of consumption patterns. Applied Economics, 25(9): 1245-1259.

Seo, S.C. and O. Capps (1997): Regional variability of price and expenditure elasitcities: The case of spaghetti sauces. *Agribusiness*, 13 (6): 659-672.

Shonkwiler, J.S., Yen, S.T. (1999). Two-step estimation of a censored system of equations. *American Journal of Agricultural Economics*, 81(4): 972-982.

Sornpaisarn, B., Shield, K., Cohen, J., Schwartz, R., Rehm, J. (2013). Elasticity of Alcohol Consumption, Alcohol-related Harms, and Drinking Initiation in Low- and Middle-Income Countries: A Systematic Review and Meta-analysis. *International Journal of Alcohol and Drug Research*, 2(1): 45-58.

Stanley, T.D. (2008). Meta-regression methods for detecting and estimating empirical effects in the presence of publication selection. *Oxford Bulletin of Economics and Statistics*, 70(1): 103-127.

Stanley, T.D. (2005). Beyond publication bias. *Journal of Economic Surveys*, 19(3): 309-345.

Stanley, T.D., Doucouliagos, H. (2014). Meta-regression approximations to reduce publication selection bias. *Research Synthesis Methods*, 5(1): 60-78.

Stanley, T.D., Doucouliagos, H., Giles, M., Heckemeyer, J.H., Johnston, R.J, Laroche, P., Nelson, J.P., Paldam, M., Poot, J., Pugh, G., Rosenberger, R.S., Rost, K. (2013). Meta-Analysis of Economic Research Reporting Guidelines. *Journal of Economic Surveys*, 27(2): 390-394.

Stanley, T.D., Jarrell, S.B. (1989). Meta-regression analysis: a quantitative method of literature surveys. *Journal of Economic Surveys*, 3(2): 161-170.

Sutton, A., Duval, S., Tweedie, R., Abrams, K., Jones, D. (2000). Empirical Assessment of effect of publication bias on meta-analyses. *British Medical Journal*, 320(7249): 1574-1577.

Timmer, C.P., Falcon, W.P., Pearson, S.R. (1983). *Food policy analysis*. World Bank/Johns Hopkins Johns Hopkins University Press. Baltimore, 301 p.

Theil, H. (1965). The information approach to demand analysis. *Econometrica: Journal of the Econometric Society*, 33(1): 67-87.

Tyers, R., Anderson, K. (1992). *Disarray in world food markets*. Cambridge Books, 284 p.

USDA. (2005). *Commodity and food elasticities*. Accessed May 2015. Available at https://www.ers.usda.gov/data-products/commodity-and-food-elasticities/

Valin, H. , Sands, R.D., van der Mensbrugghe, D. , Nelson, G.C., Ahammad, H. , Blanc, E. , Bodirsky, B. , Fujimori, S. , Hasegawa, T. , Havlik, P. , Heyhoe, E. , Kyle, P. , Mason-D'Croz, D. , Paltsev, S. , Rolinski, S. , Tabeau, A. , van Meijl, H. , von Lampe, M., Willenbockel, D. (2014). The future of food demand: understanding differences in global economic models. *Agricultural Economics*, 45(1): 51-67.

Wagenaar A.C., Salois M.J., Komro, K.A. (2009). Effects of beverage alcohol price and tax levels on drinking: a meta-analysis of 1003 estimates from 112 studies. *Addiction*, 104(2): 179-190.

Wales, T.J., Woodland, A.D. (1983). Estimation of consumer demand systems with binding non-negativity constraints. *Journal of Econometrics*, 21(3): 263-285.

Yen, S.T., Lin, B.H., Smallwood, D.M. (2003). Quasi-and simulated-likelihood approaches to censored demand systems: food consumption by food stamp recipients in the United States. *American Journal of Agricultural Economics*, 85(2): 458-478.

Yu, W., Hertel, T.W., Preckel, P.V., Eales, J.S. (2004). Projecting world food demand using alternative demand systems. *Economic Modelling*, 21(1): 99-129.

Appendix 1: primary studies included in the database

Provision of food demand elasticities for a complete set of food products

Abdulai, A. (2002): Household demand for food in Switzerland. A quadratic almost ideal demand system, *Swiss Journal of Economics and Statistics* 138 (1): 1-122.

Abdulai, A. and D. Aubert (2004): A cross-section analysis of household demand for food and nutrients in Tanzania, *Agricultural economics* 31 (1): 67-79.

Abdulai, A., Jain, D.K. and A.K. Sharma (1999): Household food demand analysis in India, *Journal of agricultural econom*ics 50 (2): 316-327.

Agbola, F.F. (2003): Estimation of food demand patterns in South Africa based on a survey of households, *Journal of Agricultural and Applied Economics* 35 (3): 663-682.

Akbay, C., Boz, I. and W.S. Chern (2007): Household food consumption in Turkey, *European Review of Agricultural Economics* 34 (2): 209-231.

Alfonzo, L. and H.H. Peterson (2006): Estimating food demand in Paraguay from household survey data, *Agricultural Economics* 34 (3): 243-257.

Balisacan, A.M. (1994): Demand for food in the Philippines: responses to price and income changes, *Philippine Review of Economics and Business* 31 (2): 137-163.

Burney, N.A. and M. Akmal (1991): Food demand in Pakistan: An application of the extended linear expenditure system, *Journal of agricultural economics* 42 (2): 185-195.

Cupak, A., Pokrivcak, J., Rizov, M., Alexandri, C. and L. Luca (2014): Economic development and food demand in Central and Eastern European countries: The case of Romania. Paper prepared for Presentation at the 142nd European Association of Agricultural Economists Seminar, May 29-30, 2014, Budapest, Hungary.

Durham, C. and J. Eales (2006): Demand elasticities for fresh fruit at the retail level. Selected Paper prepared for presentation at the American Agricultural Economics Association Annual Meeting, Long Beach, July 23-26, 2006, California.

Ecker, O. and M. Qaim (2008): Income and price elasticities of food demand and nutrient consumption in Malawi. Paper prepared for Presentation at the American Agricultural Economics Association Annual Meeting, July 27-29, 2008, Orlando, FL.

Fan, S., Cramer, G. and E. Wailes (1994): Food demand in rural China: evidence from rural household survey, *Agricultural Economics* 11 (1): 61-69.

Fan, S., Wailes, E.J. and G.L. Cramer (1995): Household demand in rural China: a two-stage LES-AIDS model, *American Journal of Agricultural Economics* 77 (1): 54-62.

Gao, X.M., Wailes, E.J. and G.L. Cramer (1996): A two-stage rural household demand analysis: Microdata evidence from Jiangsu Province, China, *American Journal of Agricultural Economics* 78 (3): 604-613.

Gould, B.W. (2002): Household composition and food expenditures in China, *Agribusiness* 18 (3): 387-407.

Gould, B.W. and D. Dong (2004): Product quality and the demand for food: the case of urban China. Paper prepared for Presentation at the Annual meeting, American Agricultural Economics Association (New Name 2008: Agricultural and Applied Economics Association) August 1-4, Denver, CO (No. 20010).

Guo, X., Popkin, B.M., Mroz, T.A. and F. Zhai (1999): Food price policy can favorably alter macronutrient intake in China, *The Journal of Nutrition* 129 (5): 994-1001.

Han, T., Cramer, G.L. and T.I. Wahl (1997): Rural household food consumption in China: evidence from the Rural Household Survey. Paper prepared for Presentation at the 1997 WAEA Meeting July 13-16, Reno, NY.

Huang, J. and S. Rozelle (1998): Market development and food demand in rural China, *China Economic Review* 9 (1): 25-45.

Huang, K.S. (1985): US demand for food: A complete system of price and income effects. Washington, DC: US Department of Agriculture, Economic Research Service. Technical bulletin 1714.

Huang, K.S. and B.H. Lin (2000): Estimation of food demand and nutrient elasticities from household survey data. Washington, DC: US Department of Agriculture, Economic Research Service. Technical Bulletin No. 1887.

Jensen, H.H. and J. Manrique (1998): Demand for food commodities by income groups in Indonesia, Applied Economics 30 (4): 491-501.

Kumar, P., Kumar A., Parappurathu, S. and S.S. Raju (2011): Estimation of demand elasticity for food commodities in India, *Agricultural Economics Research Review* 24 (1): 1-14.

Liu, K.E. and W.S. Chern (2003): Food demand in urban China: an application of a multi-stage censored demand system. Paper prepared for Presentation at the Annual Meeting of the American Agricultural Economic Association, Montreal, Canada. 27-30.

Mergos, G.J. and G.S. Donatos (1989): Demand for food in Greece: An almost ideal demand system analysis, *Journal of Agricultural Economics* 40 (2): 178-184.

Mhurchu N.C., Eyles H., Schilling C., Yang Q., Kaye-Blake W., Genç M and T. Blakely (2013): Food prices and consumer demand: differences across income levels and ethnic groups, *PLoS ONE* 8(10): e75934.

Min, I., Fang, C. and Q. Li (2004): Investigation of patterns in food-away-from-home expenditure for China, *China Economic Review* 15 (4): 457-476.

Mittal, S. (2006): Structural shift in demand for food: Projections for 2020. ICRIER Working Paper. 184

Molina, J.-A. (1994): Food demand in Spain: An application of the almost ideal system, *Journal of Agricultural Economics* 45 (2): 252-258.

Muhammad, A. Seale, J.L., Meade, B. and A. Regmi (2011): International Evidence on Food Consumption Patterns: An Update Using 2005 International Comparison Program Data. USDA-ERS Technical Bulletin No. 1929.

Pitt, M.M. (1983): Food preferences and nutrition in rural Bangladesh, *The Review of Economics and Statistics* 65 (1): 105-114.

Rickertsen, K. (1998): The demand for food and beverages in Norway, *Agricultural economics* 18 (1): 89-100.

Sahn, D.E. (1988): The effect of price and income changes on food-energy intake in Sri Lanka, *Economic Development and Cultural Change* 36 (2): 315-340.

Seale, J.L., Regmi, A. and J. Bernstein (2003): International evidence on food consumption patterns. USDA Technical Bulletin No. TB-1904. 70.

Shono, C., Suzuki, N. and H.M. Kaiser (2000): Will China's diet follow western diets? *Agribusiness* 16 (3): 271-279.

Tiffin, A. and R. Tiffin (1999): Estimates of food demand elasticities for Great Britain: 1972–1994, *Journal of Agricultural Economics* 50 (1): 140-147.

Udoh, E.J., Mbossoh, E.R., Udoh, E.S. and S.B. Akpan (2013): The structure of food demand in urban city of Nigeria: An application of a Linearized Almost Ideal Demand System (LA/AIDS)], *Journal of Development and Agricultural Economics* 5 (1): 12-18.

Yan, W. and W.S. Chern (2005): Estimating food demand in rural China under the perspectives of agricultural household models. Paper prepared for Presentation at the American Agricultural Economics Association Annual Meeting, Providence, Rhode Island, USA. http://ageconsearch. umn. edu/bitstream/19171/1/sp05ya02. pdf.

Yen, S.T., Fang, C. and S.J. Su (2004): Household food demand in urban China: a censored system approach, *Journal of Comparative Economics* 32 (3): 564-585.

Zhang, W. and Q. Wang (2003): Changes in China's urban food consumption and implications for trade. Paper prepared for Presentation at the American Agricultural Economics Association annual meeting, July. Montreal, Canada. 27-30.

Zhang, X., Mount, T.D. and R.N Boisvert. (2001): The demand for food grain in China: New insights into a controversy, *Agricultural and Resource Economics Review* 30 (1): 1-9.

Provision of food demand elasticities for one food sector

Crutchfield, S.R. (1985): An econometric model of the market for New England groundfish, *Northeast Journal of Agricultural and Resource Economics* 14: 128-143.

Fang, C. and J.C. Beghin (2002): Urban demand for edible oils and fats in China: Evidence from household survey data, *Journal of Comparative Economics* 30 (4): 732-753.

Fulponi, L. (1989): The almost ideal demand system: An application to food and meat groups for France, *Journal of Agricultural Economics* 40 (1): 82-92.

Gallet, C.A. and J.A. List (1998): Elasticities of beer demand revisited, *Economics Letters* 61 (1): 67-71.

Gould, B.W. (1996): Factors affecting US demand for reduced-fat fluid milk, *Journal of Agricultural and Resource Economics* 21 (1): 68-81.

Gould, B.W., Cox, T.L. and F. Perali (1991): Demand for food fats and oils: the role of demographic variables and government donations, *American Journal of Agricultural Economics* 73 (1): 212-221.

Han, T. and T.I. Wahl (1998): China's rural household demand for fruit and vegetables, *Journal of Agricultural and Applied Economics* 30: 141-150.

Han, T., Wahl, T.I. and R.C. Mittelhammer (1998): Rural household fruit and vegetable consumption in China. Paper prepared for Presentation at the 1998 Annual meeting, American Agricultural Economics Association (New Name 2008: Agricultural and Applied Economics Association) August 2-5, Salt Lake City, UT (No. 20854).

Heien, D. and G. Pompelli (1988): The demand for beef products: cross-section estimation of demographic and economic effects, *Western Journal of Agricultural Economics* 13 (1): 37-44.

Helen, D. and L.S. Willett, (1986): The demand for sweet spreads demographic and economic effects for detailed commodities, *Northeastern Journal of Agricultural and Resource Economics* 15 (2): 160-167.

Jabarin, A.S. (2005): Estimation of meat demand system in Jordan: an almost ideal demand system, *International Journal of consumer studies* 29 (3): 232-238.

Lee, J.Y., Brown, M.G. and J.L. Seale (1992): Demand relationships among fresh fruit and juices in Canada, *Review of Agricultural Economics* 14 (2): 255-262.

Lusk, J.L., Marsh, T.L., Schroeder, T.C. and J.A. Fox (2001): Wholesale demand for USDA quality graded boxed beef and effects of seasonality, *Journal of Agricultural and Resource Economics* 26 (1): 91-106.

Ma, H., Huang, J., Rozelle, S. and A. Rae (2003): Livestock product consumption patterns in urban and rural china. Center for Applied Economics and Policy Studies, Massey University. China Agriculture Working Paper, 1-25.

Menkhaus, D.J., St. Clair, J.S. and S. Hallingbye (1985): A reexamination of consumer buying behavior for beef, pork, and chicken, *Western Journal of Agricultural Economics* 10 (1): 116-125.

Mergenthaler, M., Weinberger, K. and M. Qaim (2009): The food system transformation in developing countries: A disaggregate demand analysis for fruits and vegetables in Vietnam, *Food Policy* 34 (5): 426-436.

Niu, L. and M. Wohlgenant (2012): A censored demand system analysis of fruits and vegetables by different income groups using micro data. Paper prepared for Presentation at the

Agricultural and Applied Economics Association's 2012 AAEA Annual Meeting, August 12-14, 2012. Seattle, Washington.

Thompson, G.D. and P.N. Wilson (1999): Market demands for bagged, refrigerated salads, *Journal of Agricultural and Resource Economics* 24 (2):463-481.

Tiffin, R. and M. Aguiar (1995): Bayesian estimation of an almost ideal demand system for fresh fruit in Portugal, *European review of agricultural economics* 22 (4): 469-480.

Wadud, Md. A. (2006): An analysis of meat demand in Bangladesh using the almost ideal demand system, *The Empirical Economics Letters* 5 (1): 29-35.

Wang, Q., Fuller, F., Hayes, D. and C. Halbrendt (1998): Chinese consumer demand for animal products and implications for US pork and poultry exports, *Journal of Agricultural and Applied Economics* 30 (1): 127-140.

Wang, Q., Halbrendt, C.C. and H.H. Jensen (1997): China's beer consumption and barley imports, *Agribusiness* 13 (1): 73-84.

Yen, S.T. and C.L. Huang (2002): Cross-sectional estimation of US demand for beef products: a censored system approach, *Journal of Agricultural and Resource Economics* 27 (2): 320-334.

Yen, S.T., Kan, K. and S.J. Su (2002): Household demand for fats and oils: two-step estimation of a censored demand system, *Applied Economics* 34 (14): 1799-1806.

Yen, S.T., Lin, B.H., Harris, J.M. and N. Ballenger (2004): Demand for differentiated vegetables. Paper prepared for Presentation at the American Agricultural Economics Association Annual Meeting, August. Denver, Colorado. 1-4.

You, Z., Epperson, J.E. and C.L. Huang (1996): A composite system demand analysis for fresh fruits and vegetables in the United States, *Journal of Food Distribution Research* 27 (3): 11-22.

Study of the impacts of advertising on the structure of food demand

Capps, O., Seo, S.C. and J.P. Nichols (1997): On the estimation of advertising effects for branded products: An application to spaghetti sauces, *Journal of Agricultural and Applied Economics* 29 (2): 291-302.

Kinnucan, H.W., Miao, Y., Xiao, H. and H.M. Kaiser (2001): Effects of advertising on US non-alcoholic beverage demand: Evidence from a two-stage Rotterdam model. In Michael R. Baye, Jon P. Nelson (ed.) Advertising and Differentiated Products (Advances in Applied Microeconomics, Volume 10) Emerald Group Publishing Limited.1-29.

Richards, T.J., Gao, X.M. and P.M. Patterson (1999): Advertising and retail promotion of Washington apples: a structural latent variable approach to promotion evaluation, *Journal of Agricultural and Applied Economics* 31 (1): 15-28.

Schmit, T.M., Dong, D., Chung, C., Kaiser, H.M. and B.W. Gould (2002): Identifying the effects of generic advertising on the household demand for fluid milk and cheese: a two-step panel data approach, *Journal of Agricultural and Resource Economics* 27 (1): 165-186.

Study of the impacts of product differentiation on the structure of food demand

Adelaja, A.O., Brumfield, R.G. and K. Lininger (1990): Product differentiation and state promotion of farm produce: An analysis of the Jersey Fresh tomato, *Journal of Food Distribution Research* 21 (3): 73-86.

Foxall, G.R, Yan, J., Oliveira-Castro, J.M. and V.K. Wells (2013): Brand-related and situational influences on demand elasticity, *Journal of Business Research* 66 (1): 73-81.

Glaser, L.K. and G.D. Thompson (2000): Demand for organic and conventional beverage milk. Paper prepared for Presentation at the Western Agricultural Economics Association Annual Meeting, June. Vancouver. British Columbia.

Glaser, L.K. and G.D. Thompson (1998): Demand for organic and conventional frozen vegetables. Paper prepared for Presentation at the Annual Meeting, No 21583, 1999 Annual meeting American Agricultural Economics Association, August 8-11, Nashville, TN.

Gould, B.W. and H.J. Villarreal (2006): An assessment of the current structure of food demand in urban China, *Agricultural Economics* 34 (1): 1-16.

Study of the impacts of health policies on the structure of food demand

Flake, O. and P.M. Patterson (1999): Health, Food Safety and Meat Demand. Paper prepared for Presentation at the AAEA Annual Meetings, August 1999, Nashville, TN.

Henneberry, S.R., Piewthongngam, K. and H. Qiang (1999): Consumer food safety concerns and fresh produce consumption, *Journal of Agricultural and Resource Economics* 24(1): 98-113.

Kinnucan, H.W., Xiao, H., Hisa, C.-J. and J.D. Jackson (1997): Effects of health information and generic advertising on US meat demand, *American Journal of Agricultural Economics* 79 (1): 13-23.

Piggott, N.E. and T.L. Marsh (2004): Does food safety information impact US meat demand? *American Journal of Agricultural Economics* 86 (1):154-174.

Smed, S., Jensen, J.D. and S. Denver (2007): Socio-economic characteristics and the effect of taxation as a health policy instrument, *Food Policy* 32 (5): 624-639.

Verbeke, W. and R.W. Ward (2001): A fresh meat almost ideal demand system incorporating negative TV press and advertising impact, *Agricultural Economics* 25 (2-3): 359-374.

Study of the impacts of structural changes on the structure of food demand

Ahmadi-Esfahani, F.Z. and R.G. Stanmore (1997): Demand for vegetables in a Chinese wholesale market, *Agribusiness* 13 (5): 549-559.

Attanasio, O., Di Maro, V., Lechene, V. and P. David (2013): Welfare consequences of food prices increases: Evidence from rural Mexico, *Journal of Development Economics* 104: 136-151.

Dahlgran, R.A. (1987): Complete flexibility systems and the stationarity of US meat demands, *Western Journal of Agricultural Economics* 12 (2): 152-163.

Haq, Z., Nazli, H. and K. Meilke (2008): Implications of high food prices for poverty in Pakistan, *Agricultural Economics* 39 (1): 477-484.

Huang, J. and H. Bouis (2001): Structural changes in the demand for food in Asia: empirical evidence from Taiwan, *Agricultural Economics* 26 (1): 57-69.

Moschini, G. and K.D. Meilke (1989): Modeling the pattern of structural change in US meat demand, *American journal of agricultural economics* 71(2): 253-261.

Pinstrup-Andersen, P. and E. Caicedo (1978): The potential impact of changes in income distribution on food demand and human nutrition, *American Journal of Agricultural Economics* 60 (3): 402-415.

Ulimwengu, J.M., Workneh, S. and Z. Paulos (2009): Impact of soaring food price in Ethiopia: Does location matter? IFPRI Discussion Paper 00846.

Wood, B.D.K., Nelson, C.H. and L. Nogueira (2012): Poverty effects of food price escalation: The importance of substitution effects in Mexican households, *Food policy* 37 (1): 77-85.

Zheng, Z. and S.R. Henneberry (2010): The impact of changes in income distribution on current and future food demand in urban China, *Journal of Agricultural and Resource Economics* 35 (1): 51-71.

Methodological focus: functional forms of demand models or econometric estimation procedures

Alston, J.M. and J.A. Chalfant (1993): The silence of the lambdas: A test of the almost ideal and Rotterdam models, *American journal of agricultural economics* 75 (2): 304-313.

Balcombe, K.G. and J.R. Davis (1996): An application of cointegration theory in the estimation of the almost ideal demand system for food consumption in Bulgaria, A*gricultural Economics* 15 (1): 47-60.

Banks, J., Blundell, R. and A. Lewbel (1997): Quadratic Engel curves and consumer demand, *Review of Economics and statistics* 79 (4): 527-539.

Bergtold, J., Akobundu, E. and E. B. Peterson (2004): The FAST method: Estimating unconditional demand elasticities for processed foods in the presence of fixed effects, *Journal of Agricultural and Resource Economics* 29 (2): 276-295.

Blanciforti, L. and R. Green (1983): An almost ideal demand system incorporating habits: an analysis of expenditures on food and aggregate commodity groups, *The Review of Economics and Statistics* 65 (3): 511-515.

Blundell, R., Pashardes, P. and G. Weber (1993): What do we learn about consumer demand patterns from micro data? *The American Economic Review* 83 (3): 570-597.

Bouis, H.E. (1996): A food demand system based on demand for characteristics: if there is 'Curvature'in the Slutsky Matrix, what do the Curves look like and why? *Journal of Development Economics* 51 (2): 239-266.

Brester, G.W. and M.K. Wohlgenant (1993): Correcting for measurement error in food demand estimation, *The Review of Economics and Statistics* 75 (2): 352-356.

Brown, M.G. (1986): The demand for fruit juices: market participation and quantity demanded, *Western Journal of Agricultural Economics* 11 (2): 179-183.

Brown, M.G. and J.Y. Lee (2000): A uniform substitute demand model with varying coefficients, *Journal of agricultural and applied economics* 32 (1): 1-10.

Bryant, H.L. and G.C. Davis (2001): Beyond the Model Specification Problem: Model and Parameter Averaging Using Bayesian Techniques. In AAEA annual meeting, Chicago, IL: 5-8.

Capps, O. (1989): Utilizing scanner data to estimate retail demand functions for meat products, *American Journal of Agricultural Economics* 71 (3): 750-760.

Carpentier, A. and H. Guyomard (2001): Unconditional elasticities in two-stage demand systems: an approximate solution, *American Journal of Agricultural Economics* 83 (1): 222-229.

Chen, K.Z. (1998): The symmetric problem in the linear almost ideal demand system, *Economics Letters* 59 (3): 309-315.

Cox, T.L. and M.K. Wohlgenant (1986): Prices and quality effects in cross-sectional demand analysis, *American Journal of Agricultural Economics* 68 (4): 908-919.

Cox, T.L., Ziemer, R.F. and J.P. Chavas (1984): Household demand for fresh potatoes: A disaggregated cross-sectional analysis, *Western Journal of Agricultural Economics* 9 (1): 41-57.

Deaton, A. (1990): Price elasticities from survey data: extensions and Indonesian results, Journal of Econometrics 44 (3): 281-309.

Deaton, A. (1989): Household survey data and pricing policies in developing countries, *The World Bank Economic Review* 3 (2): 183-210.

Dong, D., Gould, B.W. and H.M. Kaiser (2004): Food demand in Mexico: an application of the Amemiya-Tobin approach to the estimation of a censored food system, *American Journal of Agricultural Economics* 86 (4): 1094-1107.

Edgerton, D.L. (1997): Weak separability and the estimation of elasticities in multistage demand systems, *American Journal of Agricultural Economics* 79 (1): 62-79.

Fabiosa, J.F. and H.H. Jensen (2003): Usefulness of incomplete demand model in censored demand system estimation. Paper prepared for Presentation at the 2003 Annual meeting,

July 27-30, Montreal, Canada, No. 21923. American Agricultural Economics Association (New Name 2008: Agricultural and Applied Economics Association). Canada.

Golan, A., Perloff, J.M. and E.Z. Shen (2001): Estimating a demand system with nonnegativity constraints: Mexican meat demand, *Review of Economics and Statistics* 83 (3): 541-550.

Green, R. and J.M. Alston (1990): Elasticities in AIDS models, *American Journal of Agricultural Economics* 72 (2): 442-445.

Hahn, W.F. (2001): Maximum likelihood estimation of a random coefficient meat demand system. Paper prepared for Presentation at the 2001 Summer Meetings of the American Agricultural Economics Association, Chicago, IL.

Heien, D. and C.R. Wesseils (1990): Demand systems estimation with microdata: a censored regression approach, *Journal of Business and Economic Statistics* 8 (3): 365-371.

Heien, D. (1982): The structure of food demand: Interreslatedness and duality, *American Journal of Agricultural Economics* 64 (2): 213-221.

Huang, K.S. and R.C. Haidacher (1983): Estimation of a composite food demand system for the United States, *Journal of Business and Economic Statistics* 4 (1): 285-291.

Karagiannis, G., Katranidis, S. and K. Velentzas (2000): An error correction almost ideal demand system for meat in Greece, *Agricultural Economics* 22 (1): 29-35.

Kastens, T.L. and G.W. Brester (1996): Model selection and forecasting ability of theory-constrained food demand systems, *American Journal of Agricultural Economics* 78 (2): 301-312.

Kasteridis, P., Yen, S.T. and C. Fang (2011): Bayesian estimation of a censored linear almost ideal demand system: Food demand in Pakistan, *American Journal of Agricultural Economics* 93 (5): 1374-1390.

Katchova, A.L. and W.S. Chern (2004): Comparison of quadratic expenditure system and almost ideal demand system based on empirical data, *International Journal of Applied Economics* 1 (1): 55-64.

Manser, M.E. (1976): Elasticities of demand for food: an analysis using non-additive utility functions allowing for habit formation, *Southern Economic Journal* 43 (1): 879-891.

Meyerhoefer, C.D., Ranney, C.K. and D.E. Sahn (2005): Consistent estimation of censored demand systems using panel data, *American Journal of Agricultural Econo*mics 87 (3): 660-672.

Moschini, G., Moro, D. and R.D. Green (1994): Maintaining and testing separability in demand systems, *American Journal of Agricultural Economics* 76 (1): 61-73.

Okrent, A.M. and J.M. Alston (2010): Demand for food in the United States: A review of literature, evaluation of previous estimates, and presentation of new estimates of demand. Poster prepared for presentation at the Agricultural and Applied Economics Association 2010 AAEA, CAES, and WAEA Joint Annual Meeting, July 25-27, 2010. Denver, Colorado.

Park, J.L., Holcomb, R.B., Raper, K.C. and O. Capps (1996): A demand systems analysis of food commodities by US households segmented by income, *American Journal of Agricultural Economics* 78 (2): 290-300.

Pashardes, P. (1993): Bias in estimating the almost ideal demand system with the stone index approximation, *The Economic Journal* 103 (419): 908-915.

Price, D.W. and R.C. Mittelhammer (1979): A matrix of demand elasticities for fresh fruits, *Western Journal of Agricultural Economics* 4 (01): 69-86.

Reed, A.J., Levedahl J.W. and C. Hallahan (2005): The generalized composite commodity theorem and food demand estimation, *American Journal of Agricultural Economics* 87 (1): 28-37.

Seo, S.C. and O. Capps (1997): Regional variability of price and expenditure elasitcities: The case of spaghetti sauces, *Agribusiness* 13 (6): 659-672.

Shi, H., Mittelhammer, R. and T.I. Wahl (1995): Aggregate food demand analysis for a transitional economy: an application to Chinese household expenditure data, *Journal of Food Distribution Research* 26 (02): 20-27.

Timmer, C P. and H. Alderman (1979): Estimating consumption parameters for food policy analysis, *American Journal of Agricultural Economics* 61 (5): 982-987.

Wohlgenant, M.K. (1989): Demand for farm output in a complete system of demand functions, *American Journal of Agricultural Economics* 71 (2): 241-252.

Wohlgenant, M.K. (1985): Estimating cross elasticities of demand for beef, *Western Journal of Agricultural Economics* 10 (2):322-329.

Yen, S.T. and B.H. Lin (2006): A sample selection approach to censored demand systems, *American Journal of Agricultural Economics* 88 (3): 742-749.

Yen, S.T., Lin, B.H. and D.M. Smallwood (2003): Quasi-and simulated-likelihood approaches to censored demand systems: food consumption by food stamp recipients in the United States, *American Journal of Agricultural Economics* 85 (2): 458-478.

Yu, W., Hertel, T.W., Preckel, P.V. and J.S. Eales (2004): Projecting world food demand using alternative demand systems, *Economic Modelling* 21 (1): 99-129.

Appendix 2. Products mapping

Product name in primary study	Product category	Aggregation level
apple	fruits and vegetables	product level
apricot	fruits and vegetables	product level
aquatic product	meat	aggregate
asparagus	fruits and vegetables	product level
baked bean	other food products	product level
banana	fruits and vegetables	product level
barley	cereals	product level
bean	fruits and vegetables	product level
bean and product	fruits and vegetables	product level
beef	meat	product level
beef and mutton	meat	product level
beef and veal	meat	product level
biscuits	other food products	product level
bread	other food products	product level
bread and cereals	cereals	aggregate
brown bread	other food products	product level
butter	dairy products	product level
cabbage	fruits and vegetables	product level

Product name in primary study	Product category	Aggregation level
cabbage chinese	fruits and vegetables	product level
cake	other food products	product level
candy and mint	other food products	product level
canned pea	fruits and vegetables	product level
canned tomato	fruits and vegetables	product level
canned vegetable	fruits and vegetables	aggregate
cantaloupe	fruits and vegetables	product level
carrot	fruits and vegetables	product level
cassava	fruits and vegetables	product level
celery	fruits and vegetables	product level
cereal	cereals	aggregate
cereal and bakery	cereals	aggregate
cereals	cereals	aggregate
cheese	dairy products	product level
cheese total	dairy products	product level
cherry	fruits and vegetables	product level
cherry sweet	fruits and vegetables	product level

Product name in primary study	Product category	Aggregation level
chicken	meat	product level
chive	fruits and vegetables	product level
chocolate	other food products	product level
citrus	fruits and vegetables	product level
citrus fruit	fruits and vegetables	product level
coarse grain	cereals	aggregate
cocoa mix and milk flavored	other food products	product level
coconut	fruits and vegetables	product level
corn	cereals	product level
crucifer	fruits and vegetables	product level
cucumber	fruits and vegetables	product level
dairy	dairy products	aggregate
dairy product	dairy products	aggregate
dairy product and egg	other food products	aggregate
dried bean	fruits and vegetables	product level
dried fruit	fruits and vegetables	aggregate
dried vegetable	fruits and vegetables	aggregate
egg	other food products	product level

Product name in primary study	Product category	Aggregation level
egg and milk	other food products	aggregate
eggplant	fruits and vegetables	product level
eggs	other food products	product level
fat	other food products	product level
fish	meat	aggregate
flour	other food products	product level
foliage	cereals	product level
fresh fruit	fruits and vegetables	aggregate
fresh milk product	dairy products	aggregate
fresh potato	fruits and vegetables	product level
fresh tomato	fruits and vegetables	product level
fresh vegetable	fruits and vegetables	aggregate
fresh vegetable	fruits and vegetables	aggregate
fresh vegetable dark green deep yellow	fruits and vegetables	aggregate
frozen vegetable	fruits and vegetables	aggregate
fruit	fruits and vegetables	aggregate
fruit and vegetable	fruits and vegetables	aggregate

Product name in primary study	Product category	Aggregation level
fruit shelf stable	fruits and vegetables	aggregate
fruits	fruits and vegetables	aggregate
garlic	fruits and vegetables	product level
gelatin pudding mix	other food products	product level
ginger	fruits and vegetables	product level
grain	cereals	aggregate
grain and cereal	cereals	aggregate
grain food	cereals	aggregate
grape	fruits and vegetables	product level
grapefruit	fruits and vegetables	product level
green pepper	fruits and vegetables	product level
green vegetable	fruits and vegetables	product level
groundnuts	fruits and vegetables	product level
honey	other food products	product level
Ice cream yogurt	dairy products	product level
icecream	dairy products	product level
Icecream yogurt	dairy products	product level
jam	other food products	product level

Product name in primary study	Product category	Aggregation level
jam and jelly	other food products	product level
jam honey chocolate	other food products	aggregate
jelly	other food products	product level
jersey tomato fresh	fruits and vegetables	product level
ketchup	other food products	product level
leafy vegetable	fruits and vegetables	product level
legume	fruits and vegetables	product level
lemon	fruits and vegetables	product level
lentil	fruits and vegetables	product level
lettuce	fruits and vegetables	product level
lettuce iceberg	fruits and vegetables	product level
maize	cereals	product level
margarine	other food products	product level
mayonnaise	other food products	product level
meat	meat	aggregate
meat and fish	meat	aggregate
meat dairy	other food products	aggregate
meat fish eggs	other food products	aggregate
melon	fruits and vegetables	product level

Product name in primary study	Product category	Aggregation level
milk	dairy products	product level
milk and dairy products	dairy products	aggregate
milk cheese and eggs	other food products	aggregate
milk powder	dairy products	product level
mix	other food products	product level
molasses	other food products	product level
muffin and roll	other food products	product level
mutton	meat	product level
mutton and lamb	meat	product level
nectarine	fruits and vegetables	product level
non beef	meat	product level
Non pork	meat	product level
Non poultry	meat	product level
Nut	fruits and vegetables	product level
nut snack	other food products	product level
oil	other food products	product level
oil and fat	other food products	product level
oil cooking	other food products	product level
oil edible	other food products	product level
oilandfat	other food products	product level
oilcooking	other food products	product level
oils and fats	other food products	product level
oilseed	other food products	product level

Product name in primary study	Product category	Aggregation level
onion	fruits and vegetables	product level
onion dry	fruits and vegetables	product level
onion spring	fruits and vegetables	product level
onions	fruits and vegetables	product level
onionspring	fruits and vegetables	product level
orange	fruits and vegetables	product level
other cereals	cereals	aggregate
other chicken	meat	product level
other fat	other food products	product level
other fresh fruit	fruits and vegetables	aggregate
other fresh vegetable	fruits and vegetables	aggregate
other fresh vegetable	fruits and vegetables	aggregate
other fruit	fruits and vegetables	aggregate
other fruit	fruits and vegetables	aggregate
other grain	cereals	aggregate
other meat	meat	product level

Product name in primary study	Product category	Aggregation level
other milk	dairy products	product level
other milk product	dairy products	aggregate
other processed vegetable	fruits and vegetables	product level
other tomato	fruits and vegetables	product level
other vegetable	fruits and vegetables	aggregate
pasta	other food products	product level
pea	fruits and vegetables	product level
peach	fruits and vegetables	product level
peanut butter	other food products	product level
peanut oil	other food products	product level
pear	fruits and vegetables	product level
peasandsoybean	fruits and vegetables	product level
pepper	fruits and vegetables	product level
pepper green	fruits and vegetables	product level
plum	fruits and vegetables	product level
popcorn	other food products	product level
pork	meat	product level

Product name in primary study	Product category	Aggregation level
pork other	meat	product level
potato	fruits and vegetables	product level
potatoes	fruits and vegetables	product level
poultry	meat	product level
poultry and fish	meat	aggregate
processed cereal	cereals	aggregate
processed fruit	fruits and vegetables	aggregate
processed meat	meat	aggregate
processed potato	fruits and vegetables	product level
processed vegetable	fruits and vegetables	aggregate
processed vegetable dark green deep yellow	fruits and vegetables	aggregate
processed wheat	cereals	
prune and plum	fruits and vegetables	product level
pulse	fruits and vegetables	product level
pulses	fruits and vegetables	product level
pumpkins	fruits and vegetables	product level
rapeseed oil	other food products	product level

Product name in primary study	Product category	Aggregation level
red meat	meat	product level
rice	cereals	product level
root	fruits and vegetables	product level
roots	fruits and vegetables	product level
salad dressing	other food products	product level
saladbagged	fruits and vegetables	product level
sauce and marinade	other food products	product level
seafood	meat	aggregate
seasoning preservative	other food products	product level
shortening	other food products	product level
sorghum	cereals	product level
sour cream	dairy products	product level
sourcream	dairy products	product level
soy oil	other food products	product level
soybean	other food products	product level
spaghetti sauce	other food products	product level
spices	fruits and vegetables	product level
strawberry	fruits and vegetables	product level
sugar	other food products	product level
sugarnadsweets	other food products	product level
sweet	other food products	product level

Product name in primary study	Product category	Aggregation level
sweetener	other food products	product level
syrup	other food products	product level
tangerine	fruits and vegetables	product level
tofu	other food products	product level
tomato	fruits and vegetables	product level
tomato fresh	fruits and vegetables	product level
tomato processed	fruits and vegetables	product level
tuber	fruits and vegetables	product level
turkey	meat	product level
veal	meat	product level
vegetable	fruits and vegetables	aggregate
vegetable oil	other food products	product level
vegetable root	fruits and vegetables	product level
vegetable shelf stable	fruits and vegetables	aggregate
vegetables	fruits and vegetables	aggregate
vegetables and fruits	fruits and vegetables	aggregate

Product name in primary study	Product category	Aggregation level
watermelon	fruits and vegetables	product level
wheat	cereals	product level
white bread	other food products	product level
white meat	meat	product level
yogurt	dairy products	product level

Appendix 3. Mapping between countries codes and world regions

Country name	ISO3 code	Region
Afghanistan	AFG	Other Asian
Albania	ALB	Former Soviet Union
Algeria	DZA	North Africa
American Samoa	ASM	Oceania
Andorra	AND	European Union
Angola	AGO	Sub-Saharan Africa
Anguilla	AIA	Latin America
Antigua and Barbuda	ATG	Latin America
Argentina	ARG	Latin America
Armenia	ARM	Former Soviet Union
Aruba	ABW	Latin America
Australia	AUS	Oceania
Austria	AUT	European Union
Azerbaijan	AZE	Former Soviet Union
Bahamas, The	BHS	Latin America
Bahrain	BHR	Middle East
Bangladesh	BGD	Other Asian
Barbados	BRB	Latin America
Belarus	BLR	Former Soviet Union
Belgium	BEL	European Union
Belize	BLZ	Latin America
Benin	BEN	Sub-Saharan Africa
Bermuda	BMU	Latin America
Bhutan	BTN	Other Asian
Bolivia	BOL	Latin America
Bosnia and Herzegovina	BIH	Former Soviet Union
Botswana	BWA	Sub-Saharan Africa
Brazil	BRA	Latin America
British Virgin Islands	VGB	Latin America
Brunei	BRN	Other Asian
Bulgaria	BGR	European Union
Burkina Faso	BFA	Sub-Saharan Africa
Burundi	BDI	Sub-Saharan Africa
Cambodia	KHM	Other Asian
Cameroon	CMR	Sub-Saharan Africa
Canada	CAN	North America
Cape Verde	CPV	Sub-Saharan Africa
Cayman Islands	CYM	Latin America
Central African Republic	CAF	Sub-Saharan Africa
Chad	TCD	Sub-Saharan Africa
Chile	CHL	Latin America
China	CHN	AsiaEast
Christmas Island	CXR	Other Asian
Cocos (Keeling) Islands	CCK	Other Asian
Colombia	COL	Latin America
Comoros	COM	Sub-Saharan Africa
Congo, Republic of the	COG	Sub-Saharan Africa
Cook Islands	COK	Oceania
Costa Rica	CRI	Latin America
Cote d'Ivoire	CIV	Sub-Saharan Africa
Croatia	HRV	Former Soviet Union
Cuba	CUB	Latin America
Cyprus	CYP	European Union
Czech Republic	CZE	European Union
Denmark	DNK	European Union
Djibouti	DJI	Sub-Saharan Africa
Dominica	DMA	Latin America
Dominican Republic	DOM	Latin America

Country name	ISO3 code	Region
Ecuador	ECU	Latin America
Egypt	EGY	Middle East
El Salvador	SLV	Latin America
Equatorial Guinea	GNQ	Sub-Saharan Africa
Eritrea	ERI	Sub-Saharan Africa
Estonia	EST	European Union
Ethiopia	ETH	Sub-Saharan Africa
Falkland Islands (Islas Malvinas)	FLK	Latin America
Faroe Islands	FRO	Other European
Fiji	FJI	Oceania
Finland	FIN	European Union
France	FRA	European Union
French Guiana	GUF	Latin America
French Polynesia	PYF	Oceania
Gabon	GAB	Sub-Saharan Africa
Gambia, The	GMB	Sub-Saharan Africa
Georgia	GEO	Former Soviet Union
Germany	DEU	European Union
Ghana	GHA	Sub-Saharan Africa
Gibraltar	GIB	Other European
Greece	GRC	European Union
Greenland	GRL	North America
Grenada	GRD	Latin America
Guadeloupe	GLP	Latin America
Guam	GUM	Oceania
Guatemala	GTM	Latin America
Guernsey	--	European Union
Guinea	GIN	Sub-Saharan Africa
Guinea-Bissau	GNB	Sub-Saharan Africa
Guyana	GUY	Latin America
Haiti	HTI	Latin America
Holy See (Vatican City)	VAT	Other European
Honduras	HND	Latin America
Hungary	HUN	European Union
Iceland	ISL	Other European
India	IND	Other Asian
Indonesia	IDN	Other Asian
Iran	IRN	Middle East
Iraq	IRQ	Middle East
Ireland	IRL	European Union
Israel	ISR	Middle East
Italy	ITA	European Union
Jamaica	JAM	Latin America
Jan Mayen	--	Other European
Japan	JPN	AsiaEast
Jersey	--	European Union
Jordan	JOR	Middle East
Kazakhstan	KAZ	Former Soviet Union
Kenya	KEN	Sub-Saharan Africa
Kiribati	KIR	Oceania
Korea, North	PRK	AsiaEast
Korea, South	KOR	AsiaEast
Kuwait	KWT	Middle East
Kyrgyzstan	KGZ	Former Soviet Union
Laos	LAO	Other Asian
Latvia	LVA	European Union
Lebanon	LBN	Middle East
Lesotho	LSO	Sub-Saharan Africa
Liberia	LBR	Sub-Saharan Africa
Libya	LBY	North Africa

Country name	ISO3 code	Region
Liechtenstein	LIE	Other European
Lithuania	LTU	European Union
Luxembourg	LUX	European Union
Macedonia	MKD	Former Soviet Union
Madagascar	MDG	Sub-Saharan Africa
Malawi	MWI	Sub-Saharan Africa
Malaysia	MYS	Other Asian
Maldives	MDV	Other Asian
Mali	MLI	Sub-Saharan Africa
Malta	MLT	European Union
Man, Isle of	--	European Union
Marshall Islands	MHL	Oceania
Martinique	MTQ	Latin America
Mauritania	MRT	Sub-Saharan Africa
Mauritius	MUS	Sub-Saharan Africa
Mayotte	MYT	Sub-Saharan Africa
Mexico	MEX	North America
Micronesia, Federated States of	FSM	Oceania
Moldova	MDA	Former Soviet Union
Monaco	MCO	European Union
Mongolia	MNG	Former Soviet Union
Montserrat	MSR	Latin America
Morocco	MAR	North Africa
Mozambique	MOZ	Sub-Saharan Africa
Myanmar (Burma)	MMR	Other Asian
Namibia	NAM	Sub-Saharan Africa
Nauru	NRU	Oceania
Nepal	NPL	Other Asian
Netherlands	NLD	European Union
Netherlands Antilles	ANT	Latin America
New Caledonia	NCL	Oceania
New Zealand	NZL	Oceania
Nicaragua	NIC	Latin America
Niger	NER	Sub-Saharan Africa
Nigeria	NGA	Sub-Saharan Africa
Niue	NIU	Oceania
Norfolk Island	NFK	Oceania
Northern Mariana Islands	MNP	Oceania
Norway	NOR	Other European
Oman	OMN	Middle East
Pakistan	PAK	Other Asian
Palau	PLW	Oceania
Palestine	--	Middle East
Panama	PAN	Latin America
Papua New Guinea	PNG	Oceania
Paraguay	PRY	Latin America
Peru	PER	Latin America
Philippines	PHL	Other Asian
Pitcairn Islands	PCN	Oceania
Poland	POL	European Union
Portugal	PRT	European Union
Puerto Rico	PRI	Latin America
Qatar	QAT	Middle East
Reunion	REU	Sub-Saharan Africa
Romania	ROM	European Union
Russia	RUS	Former Soviet Union
Rwanda	RWA	Sub-Saharan Africa
Saint Kitts and Nevis	KNA	Latin America
Saint Lucia	LCA	Latin America
Saint Pierre and Miquelon	SPM	North America

Country name	ISO3 code	Region
Saint Vincent and the Grenadines	VCT	Latin America
San Marino	SMR	Other European
Sao Tome and Principe	STP	Sub-Saharan Africa
Saudi Arabia	SAU	Middle East
Senegal	SEN	Sub-Saharan Africa
Serbia and Montenegro	--	Former Soviet Union
Seychelles	SYC	Sub-Saharan Africa
Sierra Leone	SLE	Sub-Saharan Africa
Singapore	SGP	Other Asian
Slovakia	SVK	European Union
Slovenia	SVN	European Union
Solomon Islands	SLB	Oceania
Somalia	SOM	Sub-Saharan Africa
South Africa	ZAF	Sub-Saharan Africa
Spain	ESP	European Union
Sri Lanka	LKA	Other Asian
Sudan	SDN	North Africa
Suriname	SUR	Latin America
Svalbard	SJM	Other European
Swaziland	SWZ	Sub-Saharan Africa
Sweden	SWE	European Union
Switzerland	CHE	Other European
Syria	SYR	Middle East
Taiwan	TWN	AsiaEast
Tajikistan	TJK	Former Soviet Union
Tanzania	TZA	Sub-Saharan Africa
Thailand	THA	Other Asian
Togo	TGO	Sub-Saharan Africa
Tokelau	TKL	Oceania
Tonga	TON	Oceania
Trinidad and Tobago	TTO	Latin America
Tunisia	TUN	North Africa
Turkey	TUR	Middle East
Turkmenistan	TKM	Former Soviet Union
Turks and Caicos Islands	TCA	Latin America
Tuvalu	TUV	Oceania
Uganda	UGA	Sub-Saharan Africa
Ukraine	UKR	Former Soviet Union
United Arab Emirates	ARE	Middle East
United Kingdom	GBR	European Union
United States	USA	North America
Uruguay	URY	Latin America
Uzbekistan	UZB	Former Soviet Union
Vanuatu	VUT	Oceania
Venezuela	VEN	Latin America
Vietnam	VNM	Other Asian
Virgin Islands	VIR	Latin America
Wallis and Futuna	WLF	Oceania
Western Sahara	ESH	North Africa
Western Samoa	WSM	Oceania
Yemen	YEM	Middle East
Zaire (Dem Rep of Congo)	ZAR	Sub-Saharan Africa
Zambia	ZWB	Sub-Saharan Africa
Zimbabwe	ZWE	Sub-Saharan Africa

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