Systematic review and meta-regression of food price elasticities – do methods of demand analysis matter?

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INTRODUCTION

Food prices and consumers responses to changes in food prices have gained lot of attention in the past few years. In low income countries there are concerns on how fluctuations in food prices affect rates of malnutrition and nutrient deficiencies (Ruel et al. 2010, Mazzocchi et al. 2012) whereas in the middle- and high-income countries the debate is ongoing on how food-price-based public health measures could help populations to switch to healthier diets and hence reduce the burden from obesity and related chronic conditions (Mytton et al. 2012).

The measure of food price elasticity of demand is the standard instrument to analyse consumers' responses to food price changes. Price elasticities are in general estimated from demand functions, which can range from simple demand equations for particular foods to complete demand systems covering the whole range of consumer goods. The wide range of methods and functional forms, differing levels of complexity and reports on known sources of bias in demand system estimations (Deaton 1988, Cox and Wohlgenant 1986, Shonkwiler and Yen 1999) have led us to question if, and to what extent, there exist systematic differences in the estimated price elasticity values depending on the methods used in the demand analyses. To answer this question we have used a database of food price elasticities gathered from a systematic review of literature (Green et al. 2013, Cornelsen et al. 2013) and use a meta-regression analysis to investigate the influence of various methodological aspects on the estimates of both own- and cross-price elasticities.

We found two other papers that have done such an analysis for own-price elasticities of meat (Gallet 2010) and fish (Gallet 2009). The results of these studies showed that the own-price elasticity of fish is sensitive to demand specification, data issues, estimation method, and publication characteristics whereas in the meta-regression of meat own-price elasticities study-level effects were found to be significant and estimates varied significantly depending on specifications and estimation methods, as well as publication type.

This paper is the first to do a meta-regression analysis across the whole range of food groups. In following we first describe the systematic review from which the food price elasticities are sourced. We then proceed to discuss the methodological differences that are likely to affect the estimates of price elasticities and subsequently present the meta-regression model and its results, followed by a concluding discussion.

METHODS

1. Systematic literature review of food price elasticities

The database of food price elasticities, used in this study was compiled from a systematic literature review conducted with an end date in August 2011 for own-price elasticities and in November 2012 for cross-price elasticities[1]. Searches for studies were done in academic databases (ISI Web of Science, EconLit, Medline, AgEcon and Agricola) and in other online resources (Google (and Scholar), Ideas, Eldis, websites of USDA, FAO, World Bank and IFPRI).

The review included published and grey literature (with English abstract), estimating food price elasticities of demand using data from 1990 onwards and applying multiple equation methods. It includes studies that use nationally representative aggregate data (national average statistics), data from household surveys (cross-sectional) or data from longitudinal surveys[2]. It is important to note here that the inclusion criteria excluded studies estimating demand through a single equation as the focus was on demand models which are consistent with economic consumer theory requiring the estimation of demand systems. Secondly, as the criteria prescribes the inclusion of studies employing only post 1990 data, a large amount of studies employing long time series data, are excluded. While this ignores a considerable amount of past literature, it is justified as this way the elasticity estimates included are more recent and thus more relevant to current economic conditions.

From the included studies we extracted uncompensated (Marshallian) own- and cross-price elasticities into a database. These elasticities were then aggregated into nine broad categories of food – fruits and vegetables (FV); meat; fish; cereals; dairy; eggs; fats and oils (FO); sweets, confectionery and sweetened beverages (SCS); and other foods. Price elasticities for food groups at a higher aggregation level than that used in this study (e.g. ‘meat and dairy’) were excluded. We also excluded cross-price elasticities that, due to aggregation, were within one food group (e.g. cross-price elasticity of pork to beef price, or maize to rice price).

In addition to food price elasticity estimates the database includes following: whether the study is published, country and region the study is conducted in, data source and type, years

[1] The review was conducted by the authors of this study

[2] Studies using scanner data were assigned the three data categories based on the adjustments done to the data as reported by the study authors. Because of the large number of observations and significant censoring in the data, scanner data are often aggregated to monthly or annual data or across households.

of data used, frequency of the time dimension, function and estimation type used in the demand analysis, whether the demand system estimated is complete or conditional, whether and how censoring in data is controlled for, what price data is used and whether bias are addressed when unit prices are used. The database also includes information on categories used within studies such as income or profession groups. For this analysis we have averaged the price elasticities across these groups so that every price elasticity estimate represents a national average for the particular food item.

2. Methodological aspects of demand analysis

There are numerous methods available to estimate demand for consumer goods and the choice largely depends on the theoretical and empirical assumptions the researchers are willing to make and on data availability. The systematic review described above, and thus this paper, focused on research employing multiple equation methods for demand analysis, in coherence with consumer theory, prescribing that consumers allocate their fixed budget across the available bundle of goods depending on relative prices. Thus, demand functions for different goods are not independent from each other, and demand for a specific good is influenced by the price of all goods. This requires the joint estimation of demand equations as errors are correlated and cross-equation constraints exist. These demand systems can range from a subset of particular foods or beverages (e.g. different meats or non-alcoholic beverages) or it can include the whole range of consumer goods, where the former type reflects ‘conditional’ demand (i.e. subordinate to the consumer choice of purchasing that group of goods) and the latter relates to complete demand (i.e. all goods enter the consumer decision process simultaneously).

In the analysis we consider known sources of bias (described below) as well as other aspects that may have systematic influence on price elasticity estimates. There are several reasons to focus on the impact of these biases on cross-price elasticity estimates. First, corss-price elasticities are key to the analysis of substitutions across foods, which is in turn important in the analysis of nutrition outcomes. Second, given that relative prices matter in demand response, changes in own prices have a more noticeable impact as they affect all relative prices in a given equation, while the marginal impact of price change in one substitute good is harder to capture. Also, cross-price elasticities found in the literature show a high degree of heterogeneity, including switches from positive (substitute goods), to negative (complementary goods). Hence the biases can potentially cause a change in the direction of the elasticity but it will be difficult to detect because the sign of the cross-price elasticity cannot be assumed a priori for most foods.

The methodological aspects that will be considered in this study are in more detail[3]:

Different data types. The type of data used to estimate demand systems vary from aggregate time series of national food expenditure data to very detailed consumer data recorded with hand-held scanners for all purchases of sample households. The level of detail in the data can have an effect on the estimated elasticties. Cross-sectional data is unable to capture the dynamic components of consumption while time series data can suffer from aggregation bias (Denton and Mountain 2001, Blundell et al 1993). In this study we consider three types of data structure - aggregate (national average statistics including time series), household survey data (cross-sectional) and longitudinal survey data (panel). We also test whether frequency of the time dimension has an impact on the elasticity estimates. We use four categories of weekly/bi-weekly, monthly, quarterly or higher frequency/no time dimension.

Different functional forms for estimating demand systems can lead different elasticity estimates (Dameus et al. 2002). Most popular demand systems stem from the Almost Ideal Demand System (AIDS). The AIDS model is non-linear in prices, but linear in total expenditure and most studies adopt a linearized version (LA-AIDS) due to its simple implementation (Deaton and Muellbauer 1980). In more recent years the quadratic version (QAIDS) has become popular allowing for a non-linear relationship between income and expenditure across different income groups (Banks et al. 1997). However, other systems, such as Rotterdam model, translog model, normalized quadratic model, LinQuad incomplete demand system, Mixed Demand models are also used.

Different estimation methods may also determine different estimates. Because of correlated errors, demand systems are typically estimated via seemingly unrelated regression (SUR), or full information maximum likelihood (FIML). However, some studies address price and/or income expenditure by adopting instrumental variable methods (e.g. two-stage least squares (2SLS) or – more recently – dynamics are accounted for in cointegrated demand systems (VEC-AIDS).

[3] Some of these aspects were suggested by reviewers of an article written on the systematic literature review (Cornelsen et al. 2013)

Conditionality of the elasticities. Complete demand systems may be estimated in a single stage, or can be broken down in two or more subsequent stages of budget allocation. For example, Edgerton (1997) assumes a three-step budgeting decision where in the first step the decisions are made on how much is spent on foods and other non-food items (health, housing etc). In the second step the budget for foods is divided to major categories (e.g. fruits) and in the third step the budget is allocated between individual expenditure to individual food items (e.g. orange juice). Elasticities that are estimated from a single-stage complete system are unconditional (i.e. price changes of individual food items affect decisions of expenditure on all consumer goods) whereas elasticities that are estimated from demand systems only at second or third level are conditional on the expenditure at higher level (i.e. price changes affect decisions on expenditure within the food group). In principle, price elasticity estimates are not affected if food groups are indeed separable (i.e. if changes in the prices of one group do not affect directly consumption of foods in other group, but only indirectly at a higher aggregation stage). However, Edgerton (1997) reports that restricting the analysis to the last stage of multi-stage budgeting process can lead to considerable errors and suggest correction procedures which are rarely adopted. Rickertsen (1998) and Klonaris and Hallam (2003) both report deviations between conditional and unconditional elasticities indicating possible systematic differences.

Censored data. If demand systems are estimated using household level data it is likely that the dataset is censored (i.e. non-expenditure is observed). This can be due to genuine and deliberate non-consumption driven by preferences and independent from prices and incomes (e.g. vegetarianism), non-consumption during the survey period (especially for low-frequency consumptions) or non-consumption explained by price and income level (i.e. at a different price/income level consumption would occur). Including these zero-observations without corrections leads to bias the estimates of the price elasticities (Heien and Wessells, 1990). The most common approaches to address the bias is to estimate the demand in two steps (e.g. Shonkwiler and Yen, 1999) where first is the dichotomous decision on whether to consume and not and in the second stage the decision on how much to consume is taken, or include a correction term in the demand equations, based on a Heckman-type correction procedure (Heien and Wessels, 1990).

Use of unit values as price data. As price data is often missing, unit values, calculated as a ratio of expenditure to its quantity is a common type of price indicators used. It has been established that the use of unit values offers a solution to missing data and provide variability in prices that in case of using aggregate consumer or retail prices at one point in time (e.g. cross-sectional data) may not have. Unit prices also mean that there are no discrepancies between the price and consumption data (Deaton and Grosh 2000). However, unit values are affected by quality bias and may lead to inconsistent estimates because errors in unit values are correlated with errors in the expenditure share or quantity (Deaton 1988). Quality bias arise because goods purchased are generally at least to some extent aggregated (e.g. beef rather than specific cuts) and households at higher income level might be purchasing more expensive (higher quality) beef cuts compared to poorer households. Any price change is likely to affect both decisions on quantity and the quality of the foods. The approaches to adjust for this bias assume that households in the same geographical area and in the same space in time face the same prices. A basic adjustment is based on regressing unit values on household socio-demographic characteristics to disentangle the quality, quantity and price effects. (Cox and Wohlgenant 1986), while more theoretical consistent approach requires the joint estimation of quantity and quality demand functions (Deaton, 1988).

3. Meta-regression model

We estimate the meta-regression separately for own- and cross-price elasticities to be able to include an additional variable for the food group for which the price changes in the latter. For the ease of interpretation, the sample of cross-price elasticities is further separated into subsamples based on the food group of price change (e.g. all cross-price elasticities relating to the increase in the price of meat are in one subsample). We exclude the food groups ‘eggs’ and ‘other food’ from the cross-price elasticity subsample due to small numbers of observations (n=154 and n=181 respectively). We considered elasticities outside of the absolute value of three standard deviations of the mean, within the food group, to be outliers and removed these in each of the data subsets; this resulted in removal of 1.6% (n=45) and 2.4% (n=83) of the observations from own- and cross-price elasticity datasets respectively.

We first estimate a two-level random intercept model to account for study level heterogeneity where the individual elasticities represent the second level, and study, the first level [1]. To evaluate the significance of study level effects and compare the two-level model to an ordinary one-level regression model we used the likelihood ratio test. Based on the outcome of the test, we adopted the two-level model only where there was a significant likelihood gain. Standard errors were bootstrapped (50 replications) in both cases. The two-level random intercept models were fitted using maximum likelihood (ML) and single-level regressions were estimated by ordinary least squares (OLS).

$$y_{ij} = a + bx_{ij} + u_j + e_{ij} \quad [1]$$

The dependent variable (y_{ij}) in the model is the uncompensated own- or cross-price elasticity. The random components u_j and e_{ij} are first (study) and second (elasticity) level errors. It is assumed that these are uncorrelated with zero mean and normally distributed with estimated variance of σ_u^2 and σ_e^2 respectively (Rasbash et al. 2004). Independent variables (x_{ij} or x_j) include following variables (for dummy variables categories excluded are marked):

- whether study is published (**yes** (excluded)/ no)
- country income group (high, middle, **low** (excluded))
- data type used (aggregate, **household survey** (excluded), longitudinal survey)
- frequency of the data time dimension (weekly/bi-weekly, monthly, quarterly, **higher frequency/no time dimension** (excluded))
- functional form of the demand model (**AIDS** (excluded), LA-AIDS, QAIDS, other)
- estimation method (least squares (LS)[4], **seemingly unrelated regression (SUR)** (excluded), maximum likelihood (ML), other or missing).
- whether the demand system is complete (**complete** (excluded), conditional on expenditure on all foods, conditional on expenditure on individual food groups)
- how censored data is managed (data is aggregated or replaced with a simple average of existing observations, **two-step estimator** (excluded), other, not applicable, not described)
- which prices are used (**retail price[5]** (excluded), unit value – adjusted to bias[6], unit value – not adjusted to bias, other[7], not described).
- mean year (simple average of the years of data used in the study)
- food group of consumption change (cross-price elasticity subsample only) (**FV** (excluded), meat, fish, dairy, cereals, FO, SCS and eggs and other foods for own-price elasticity subsample)[8].

[4] We considered creating sub-category for 2SLS and 3SLS to separate these approaches from simple OLS but the number of elasticities estimated by 2SLS or 3SLS was too small to justify a separate dummy

[5] Retail prices or consumer price indices

[6] Any method reported, including one by Deaton (1988) and Cox and Wohlegant (1986)

[7] Mixture of unit price and retail prices; self reported prices; shadow prices; comparative price levels using PPP; ratio of nominal to real expenditure

RESULTS

1. Descriptive findings

The database includes 127 studies estimating own-price elasticities (n=2,720) for the nine food groups and 76 studies reporting cross-price elasticities (n=3,436) for the same food groups with the exception of excluding eggs and other food category[9]. Table 1 shows the distribution of the variables of interest within the dataset. A large share of own-price elasticities (66%, n=1,803) are from two multi-country studies using International Comparison Program Data (Muhammad et al. 2011; Seale et al. 2003) while for cross-price elasticities two largest studies count only for 17% of observations.

For both own- and cross-price elasticities, there are larger share of estimates from grey literature (largely conference papers). Own-price elasticities are more often estimated for low-income countries while more cross-price elasticity estimates are available from high-income countries. This is probably due to more detailed data being available from high income countries allowing for more detailed food items to be included.

Table 1. Description of data

	Own-price elasticities n=2,720		**Cross-price elasticities** n=3,436	
Variables	Obs	%	Obs	%
Study peer reviewed?				
No	2,207	81.14	2,189	63.71
Yes	513	18.86	1,247	36.29
Country Income level				
Low	42.21	42.21	865	25.17
Middle	735	27.02	790	22.99
High	837	30.77	1,781	51.83
Data type				
Aggregate	1,994	73.31	181	5.27
Household survey data	562	20.66	2,606	75.84
Longitudinal survey data	164	6.03	649	18.89
Data time dimension frequency				
Weekly/bi-weekly	82	3.01	200	5.82
Monthly	260	9.56	902	26.25
Quarterly	60	2.21	313	9.11
Higher frequency /no time dimension	2,318	85.22	2,021	58.82

[8] For FV subsample we excluded ‘meat’ category, for the remaining subsamples we excluded FV category

[9] We were unable to retrieve some of the data on methods for 9 papers. Originally the review included 136 papers estimating own-price elasticities and 79 also presenting cross-price elasticities

Demand system				
Complete	1,980	72.79	867	25.23
Conditional on food group expenditure	352	12.94	1,652	48.08
Conditional on food sub-group expenditure	388	14.26	917	26.69
Function type				
AIDS	264	9.71	1198	34.87
LA-AIDS	339	12.46	947	27.56
QAIDS	110	4.04	376	10.94
Other	2,007	73.79	915	26.63
Estimation type				
SUR	370	13.6	1,849	53.81
Least Squares	109	4.01	680	19.79
ML	1,877	69.01	10	0.29
Other	97	3.57	163	4.74
Not reported	267	9.82	734	21.36
How censoring in consumption data is managed?				
Data aggregated or missing observations replaced by average values	127	4.67	754	21.94
Two-step procedure	335	12.32	1,356	39.46
Other	34	1.25	452	13.15
Not reported	235	8.64	756	22
Not applicable (e.g. Aggregate data)	1,989	73.13	112	3.43
Which prices are used?				
Retail price or price index	160	5.88	349	10.16
Unit price (adjusted to bias)	186	6.84	711	20.69
Unit price (unadjusted to bias)	1,129	41.51	1,857	54.05
Other	1,107	40.7	290	8.44
Not reported	138	5.07	229	6.66
Food Group (price change)				
FV	464	17.06	785	22.85
Meat	461	16.95	786	22.88
Fish	369	13.57	354	10.3
Dairy	392	14.41	477	13.88
Eggs	16	0.59	n/a	n/a
Cereals	372	13.68	487	14.17
FO	302	11.1	235	6.84
Sweets	48	1.76	312	9.08
other foods	296	10.88	n/a	n/a
Food Group (consumption change)				
FV	n/a	n/a	788	22.93
Meat	n/a	n/a	781	22.73
Fish	n/a	n/a	354	10.3
Dairy	n/a	n/a	473	13.77
Cereals	n/a	n/a	479	13.94
FO	n/a	n/a	240	6.98

SCS	n/a	n/a	321	9.34
Mean Year	2000		2001	

If excluding the two above mentioned large studies, household survey data (cross-sectional) is the most common data structure. Data at higher frequency than quarterly (e.g. annual) or no time dimension is most frequent for both types of elasticities. AIDS is the most common function for demand system for cross-price elasticities and LA-AIDS is the most common for own-price elasticities, when the two large multi-country studies are excluded applying Florida-Slutsky model and hence falling to the ‘other’ category. Most common estimation type is SUR if the two big studies are not considered. Again, excluding these two studies, elasticities are most commonly estimated as conditional on expenditure for all foods (cross-price elasticities) or all non-foods (own-price elasticity).

Two-step methods are most common approach to deal with censored data but for 9% (32 studies) of own-price elasticities and 22% (23 studies) of cross-price elasticities it is not reported whether censoring is dealt with (or if it is an issue) but based on the data used is a possible problem and hence the estimates are potentially biased. However, even more worryingly 42% (44 studies) of own-price elasticities and 54% (28 studies) of cross-price elasticities are estimated using unit values as price data and for which it has not been reported whether quality or measurement bias have been adjusted for. Hence nearly a third of studies provide price elasticity estimates that are subject to possible bias.

Lastly, both own- and cross-price elasticities are most estimated for fruits and vegetables or meat. Average data year used in estimation of elasticities is 2000-2001.

2. Meta-regression results

Own-price elasticities

Table 2 presents the full meta-regression results for own-price elasticities. The LR test indicates that study level effects are statistically significant ($p<0.000$) and therefore we present the results of a two-level random intercept model.

Table 2. Meta-regression results for own-price elasticity subsample (n=2,720)

VARIABLE		*coef*	*SE*	*p-val*
Publication type	Grey literature	0.031	0.037	0.395
Income level	Middle income	0.133	0.004	<0.000
	High income	0.300	0.005	<0.000
Data type	Aggregate	0.236	0.072	0.001
	Longitudinal survey data	0.376	0.096	<0.000
Data time dimension frequency	Weekly/bi-weekly	-0.443	0.068	<0.000
	Monthly	-0.252	0.060	<0.000
	Quarterly	-0.244	0.078	0.002
Demand system	Conditional on food expenditure	-0.041	0.056	0.464
	Conditional on food sub-group expenditure	-0.184	0.064	0.004
Function type	LA-AIDS	0.061	0.101	0.547
	QAIDS	0.001	0.077	0.987
	Other	0.031	0.071	0.668
Estimation type	Least squares	-0.156	0.072	0.031
	ML	-0.191	0.060	0.001
	Other	-0.187	0.063	0.003
	Not reported	-0.059	0.041	0.151
Cons data censoring	Data aggregated/based on average	0.074	0.065	0.250
	Other	0.179	0.079	0.023
	Not reported	0.171	0.053	0.001
	Not applicable	0.206	0.062	0.001
Price type	Unit price (adjusted to bias)	-0.052	0.061	0.395
	Unit price (unadjusted to bias)	-0.054	0.045	0.232
	Other	-0.026	0.058	0.661
	Not reported	-0.034	0.063	0.589
Food Group	Meat	-0.086	0.018	<0.000
	Fish	-0.069	0.014	<0.000
	Dairy	-0.095	0.014	<0.000
	Eggs	0.134	0.065	0.039
	Cereals	0.084	0.014	<0.000
	Fats and oils	0.113	0.010	<0.000
	SCS	-0.060	0.097	0.541
	Other	-0.254	0.015	<0.000
mean year		-0.011	0.011	0.292
	Constant	21.46	21.24	0.312
Random effects parameters				
Study ID	sd(_cons)	0.327	0.022	
	sd(Residual)	0.257	0.012	
LR test vs. linear regression	chibar2(01) =	768.46		<0.000

*reference variables: FV, published study, low income country, cross-sectional data, complete demand system using AIDS function and estimated by SUR, using two-step method to adjust for censoring and using retail prices;

Most variables are statistically significant at conventional statistical significance levels either individually or jointly in its group with the exception of peer review, function type (joint significance p=0.834), price type (joint significance p=0.894) and mean year variables. Hence, the own-price elasticities do not seem to be affected by the use of price data and whether unit values are adjusted to quality bias. Also, different functional forms are not associated with significant differences in the estimated elasticities at conventional statistical significance levels.

As expected, the own-price elasticities are larger (less elastic) as country income level increases (p<0.000). Aggregate and longitudinal data are also both associated with larger elasticity estimates (p<0.001). Data with time dimension more frequent than annual is associated with smaller (more elastic) own-price elasticities (p<0.001). Elasticities conditional on food sub-group expenditure provide the smallest estimates indicating systematic differences between elasticities estimated from complete and incomplete demand systems. SUR produces larger elasticities compared to other estimation methods.

Whether or not censoring in data is addressed appears to affect the elasticity estimates although from the methods to address this 'other'[10] is associated with significant differences (p=0.023) in comparison to the two-step method. Studies where censoring is not assumed to be an issue (e.g. using aggregate data), elasticity estimates are larger. Studies that do not report whether or how censoring is addressed (but is potentially an issue due to data type used) are associated larger elasticity estimates indicating possible bias in comparison to elasticity estimates from demand systems where censoring has been addressed by a two-step method.

In comparison to FV, demand for meat, fish, dairy, sweets and sweetened beverages, and 'other' foods is more elastic whereas the demand for eggs, cereals, and FO is less elastic.

Cross-price elasticities

As it is difficult to determine a priori which sign the cross-price elasticity should be (i.e. whether foods are complements or substitutes) and the estimates are generally much smaller compared to own-price elasticity estimates, the interpretation of the meta-regression results, presented in appendix 1 is more difficult. Because of the smaller number of observations and

[10] Individual unit values replaced with median unit values by household degree of urbanization and region of residence; unit values replaced by virtual prices; predicted following the concept of opportunity values

larger share of variables that were not statistically significant at conventional levels in the full model we only present models where explanatory variables are individually or jointly (dummy variables) significant at least at 10% level[11].

Study level effects were not significant at conventional statistical significance level in none of the sub datasets and hence all are estimated with OLS as single-level models[12]. Overall, some methodological aspects do seem to affect the cross-price elasticity estimates. However, the aspects that appear influential vary across the different food groups. Estimation type and whether and how censoring is dealt with are statistically significant at conventional levels in the meta-regressions of most of food groups. Function type, mean year, type of price data and data time dimension frequency also explain some variation in the cross-price elasticities in more than half of the food groups.

Publication type and conditionality of the elasticities are found to be statistically significant only in 2-3 food groups. Data type is reported only for SCS subsample but in majority of the other sub-samples this variable was removed due to multi-collinearity issues (very high VIF factor) and therefore its significance on the elasticity estimates cannot be determined.

Across the food groups and the different methodological approaches few consistent patterns emerge. LA-AIDS is relatively consistently associated with more positive cross-price elasticities in comparison to AIDS while LS and ML estimation methods both are associated with more negative cross-price elasticities in comparison to SUR. Studies using data where censoring in the consumption is not an issue is mostly associated with more negative cross-price elasticity values.

Literature type, if included in the model is associated with more negative values however increase in the mean year value is associated with increase in the cross-price elasticity value (more positive). Whether demand system is estimated as complete or not only affected elasticities in the FV and dairy subset where the conditional (on all food expenditure) cross-price elasticities were associated with more negative values in comparison to values from a complete demand system. The type of price data was individually significant at conventional

[11] In the SCS subset some variables that were not significant at conventional levels were included as exclusion reduced the value of adjusted R^2 considerably.

[12] We also ran a model were all 7 food groups were in a single dataset and used interaction terms of variables indicating food group of price change and consumption change as explanatory variables (i.e. used a dummy variable for each cell in the cross-price elasticity matrix). Study level effects were not significant (p=0.139) in this case either.

levels in only two cases (within the FV subset), however in a further three subsets (meat, cereal and FO) price type was jointly significant ($p<0.1$). This indicates that price data jointly explains some of the variation in the cross-price elasticities. However the categories used here for price data are not individually different from each other (at conventional statistical significance levels).

DISCUSSION

The role of food prices has become prominent in developing public health policies relating to nutrition in countries of all income levels. The results of the systematic literature review show that there is an abundance of individual studies estimating price elasticity of food demand across the globe. However, only a few have attempted to synthesise this body of research which can be used in the global health policy context information (Green et al 2013, Gallet 2009, Gallet 2010, Andreyeva 2010). These syntheses have also shown the wide array of data and methods used in the estimation of price elasticities and inevitably lead to question how this affects the elasticity estimates.

We have added to the literature by using a meta-regression analysis examining how methodological differences affect own- and cross-price elasticity estimates across different food groups. In a short answer, yes, the different methodological approaches to smaller or larger extent do matter as they significantly affect food price elasticity estimates.

We found stronger evidence on the influence from methodological approaches for own-price elasticities, partly due to easier theoretical interpretation in comparison to cross-price elasticities. We draw from our results that after controlling for the food group for which the elasticity is estimated for and country income level, there are statistically significant differences in own-price elasticities estimated using different types of data at different frequencies; or estimated as conditional or unconditional, or estimated by different estimation methods. We also found evidence that if censoring in the data is not dealt with, elasticity estimates are significantly different in comparison to when the models take it into account. Interestingly we did not find evidence of significant influence on own-price elasticities stemming from the choice of functional form or the type of price data used.

The evidence on the influence of methods on cross-price elasticities is somewhat weaker. There is some support that the functional form and estimation method have systematic effect on cross-price elasticities and in fewer cases we observed significant differences due to conditionality of the elasticities and the publication type. In comparison to own-price elasticities, the sample size (across food groups) is smaller and as cross-price elasticities can vary from negative to positive, small and statistically significant changes are difficult to detect. At the same time cross-price elasticities are more susceptible to bias because they are usually not far from zero and thus even small bias can cause a switch in the direction that in the worst case can lead to a different policy suggestion. Studies using the estimates of the impact of food price changes on consumption in developed world in the context of 'fat taxes' are increasingly explicitly including cross-price effects into the estimation of health impact of these fat taxes. Therefore it is crucial that we gain insight into if and which estimates of the price elasticities are reliable and also the extent of uncertainty they come with.

A major limitation in the existing studies is that approximately half fail to report any indicators of statistical significance (SE's, p- or t- values) which leaves researchers or policy makers using the elasticity estimates with an unknown level of uncertainty that carries through simulation or modelling exercises employing these. It also makes it difficult to combine estimates from individual studies into meta-analyses that would be particularly useful if numerous studies exist in the same country that are methodologically rigorous.

In addition, there is also the issue on the level of detail regarding food items in the study that also relates back to the choice and availability of data. If we want to analyse the impact of food prices on diets and nutrition we need price elasticities for all food items estimated from the same data in a complete system. These studies are scarce as detailed data on food expenditure or consumption is rare and is usually heavily censored.

In conclusion, studies wanting to employ food price elasticities as parameters in their modelling or other excercises should be cautious in choosing where they get these from and which methods are used in the estimation. Consideration should be given to which data, from what time and at which frequency is used, whether censoring in the data has been an issue that has been dealt with and which price data is used and whether any biases arising from this choice has been addressed. If many good quality estimates are available, they should consider using meta-estimates. Sensitivity analysis allowing for uncertainty in the price elasticity (particularly cross-price elasticity because these can switch direction) estimates should also be carried out.

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Appendix 1. Meta-regression of cross-price elasticities

		FV		Meat		Cereal		Dairy		Fish		Fats and oils		SCS	
variable		**coef**	**SE**	**coef**	**SE**	**coef**	**SE**	**coef**	**SE**	**coef**	**SE**	**coef**	**SE**	**coef**	**SE**
Publication type	grey literature					-0.034	0.023			-0.104**	0.047	-0.054*	0.027		
Income level	middle income							-0.050**	0.025					-0.065*	0.038
	high income							-0.059**	0.024					-0.023	0.056
Data type	aggregate													0.188***	0.065
	longitudinal survey													0.036	0.054
Data time dimension frequency	weekly/bi-weekly			0.127**	0.062	-0.119***	0.046			0.093	0.081	0.222***	0.074		
	monthly			0.105	0.098	-0.045	0.033			0.147**	0.058	0.002	0.039		
	quarterly			0.073	0.070	0.126*	0.068			0.095	0.075	0.101	0.115		
Demand system	Cond. on all food expenditure	-0.069***	0.019					-0.073***	0.020						
	Cond. on food sub-group expenditure	0.003	0.039					-0.028	0.020						
Function type	LA-AIDS	0.013	0.012							0.070**	0.029	0.077*	0.044	0.030	0.031
	QAIDS	-0.004	0.022							0.143**	0.067	0.138**	0.054	0.003	0.037
	Other	0.030**	0.015							0.077**	0.031	0.030	0.060	-0.054	0.051
Estimation Type	least squares	-0.045**	0.020	-0.039	0.081	-0.040	0.047	0.032	0.023	-0.048	0.051	-0.050	0.030		
	ML	n/a	n/a	-0.285*	0.173			-0.034	0.030	-0.222**	0.110	-0.539*	0.337		
	other	0.023	0.023	0.067	0.091	-0.187**	0.088	-0.046	0.053	-0.037	0.052	-0.040	0.048		
	not reported	0.002	0.021	0.002	0.056	-0.058	0.050	-0.100***	0.025	0.082	0.061	-0.048	0.065		
Cons data censoring	Aggregate/average	-0.007	0.020	-0.152***	0.058	0.093**	0.045			0.001	0.057	-0.027	0.045	-0.044	0.045
	not applicable	-0.111***	0.030	-0.236***	0.067	-0.044	0.067			-0.125	0.092			0.025	0.065
	not reported	-0.023	0.023	0.035	0.058	0.022	0.040			-0.044	0.069	0.034	0.056	0.070	0.044
	other	-0.023	0.021	-0.014	0.029	0.111*	0.062			0.079***	0.026	0.118**	0.053	0.016	0.043

Appendix 1. cont.

		FV		Meat		Cereal		Dairy		Fish		Fats and oils		SCS	
variable		coef	SE	coef	SE	coef	SE	coef	SE	coef	SE	coef	SE	coef	SE
Price type	other	-0.050**	0.025	-0.024	0.060	-0.033	0.061					-0.063	0.166		
	not reported	0.013	0.029	-0.035	0.056	-0.011	0.062					-0.108	0.144		
	unit price (adjusted to bias)	0.081***	0.024	0.052	0.058	0.058	0.053					-0.028	0.146		
	unit price (unadjusted to bias)	0.001	0.024	-0.072	0.053	0.006	0.049					-0.205*	0.143		
Food Group	Meat							0.019	0.013	0.000	0.013	0.019	0.035	-0.011	0.022
	Fish	-0.003	0.010	0.048*	0.027			-0.006	0.018			0.094	0.076	-0.024	0.032
	Dairy	-0.025**	0.011	0.010	0.024					-0.011	0.011	0.086***	0.032	0.014	0.030
	Cereals	0.013	0.014	0.014	0.022			0.067**	0.027	0.036	0.030	0.048	0.034	-0.029	0.044
	Fats and oils	-0.011	0.016	-0.065*	0.038			0.048*	0.029	-0.054**	0.027			-0.133*	0.077
	SCS	0.000	0.011	-0.014	0.032			0.056**	0.026	-0.005	0.033	0.059**	0.032		
Mean year				0.008	0.004	0.007**	0.003			0.008**	0.004				
	Constant	0.024	0.025	-15.51	7.25	-14.42**	6.246	0.062**	0.027	-16.56**	8.339	0.044	0.158	0.007	0.041
	R^2	0.075		0.081		0.088		0.107		0.093		0.245		0.133	
No of observations		785		786		487		477		354		235		312	
No of studies		55		49		45		39		34		30		28	