

## **Title Page**

### **Estimating the relationship between food prices and food consumption – methods matter**

**Authors:** Laura Cornelsen<sup>ab</sup>, Mario Mazzocchi<sup>c</sup>, Rosemary Greena<sup>b</sup>, Alan D Dangour<sup>ab</sup>,  
Richard D Smith<sup>ab</sup>

<sup>a</sup>London School of Hygiene and Tropical Medicine, Keppel Street, London WC1E 7HT, UK

<sup>b</sup>Leverhulme Centre for Integrative Research on Agriculture and Health, 36 Gordon Square,  
London WC1H 0PD, UK.

<sup>c</sup>University of Bologna, Via Zamboni, 33 - 40126 Bologna, Italy

**Correspondence to be sent to:** Email: [laura.cornelsen@lshtm.ac.uk](mailto:laura.cornelsen@lshtm.ac.uk)

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## **Estimating the relationship between food prices and food consumption – methods matter**

### **ABSTRACT**

Concerns about the growing prevalence of obesity worldwide have led researchers and policy makers to investigate the potential health impact of fiscal policies, such as taxes on unhealthy foods. A common instrument to measure the relationship between food prices and food consumption is the price elasticity of demand. Using meta-regression analysis we assessed how differences in methodological approaches to estimating demand affected food price elasticities. Most methodological differences had a statistically significant impact on elasticity estimates which stresses the importance of using meta-estimates or testing the sensitivity of simulation outcomes to a range of elasticity parameters before drawing policy conclusions.

## **Introduction**

Food prices and consumers' responses to changing food prices have gained substantial attention in recent years, particularly in the context of introducing fiscal policies to tackle unhealthy diets associated with rising prevalence of obesity and non-communicable disease globally. (Basu et al. 2014, Briggs et al. 2013, Leifert and Lucina 2015, Manyema et al. 2014, NiMhurchu et al. 2015, Tiffin and Arnoult 2011, Zhen et al. 2014) These policies can include both taxes on unhealthy foods or beverages, and subsidies on healthy alternatives. Also, the potential effect of "carbon" taxes on foods, the production of which is associated with high levels of greenhouse gas emissions, is another area of growing interest where consumers' responses to relative price changes through taxes, is studied (Briggs et al. 2016, Green et al. 2015, Säll and Gren 2015, Wirsenius, Hedenus, and Mohlin 2011). To evaluate the effectiveness of this type of policies it is crucial to know the extent to which consumers change consumption patterns as a response to changes in prices.

The key instrument to predict consumer response to food price changes is the set of own- and cross-price elasticities (OPE's and CPE's). Both OPEs and CPE's are needed to estimate the impact of price changes on consumption patterns which later feed into simulation models. The own-price effect, which in the policy context, is the direct intended impact of a tax or a subsidy, is generally larger in comparison to cross-price effects. However, cross-price effects are equally important as these can reinforce the own-price effect (i.e. complement or budget effect) or work in the opposite direction (i.e. substitute effect). If substantial and significant, these less predictable indirect effects can affect policy implications of the simulation outcomes (Cornelsen et al. 2014). As an example, our previous work found that in high-income countries a 10% increase in the price of sweets (including sugar-sweetened beverages) was associated with a reduction in its consumption by 5.6% but a 3% increase in consumption of cereal, dairy and fruits and vegetables, off-setting nearly half of the calories

lost from reduced sweets consumption (Cornelsen et al. 2014). In contrast, in low-income countries, a similar price increase for sweets was associated with a 7.4% reduction in its consumption and an increase in the consumption of other foods by 6.1%. As the share of sweets in providing daily calories is much lower in low-income countries (7% in comparison to 13% in high-income countries), the substitution towards other foods, in particular cereals, far exceeded the reduction in calories from lower sweets consumption. If considering calorie intake as an outcome, the case for taxing sweets in high-income countries becomes much weaker, considering that nearly half of the calories are substituted to other sources. However, in low-income countries where under-nutrition is of concern, an increase in the price of sweets has an unexpected effect of increasing the total calories via substitution to relatively cheaper and staple foods.

In order to use price elasticities when simulating policy effects, researchers have to either use previously published estimates or estimate these from available data. While numerous studies exist estimating the demand for foods and beverages aggregated into broad groups, there is a lack of good quality evidence on specific and detailed food items, such as sugar-sweetened beverages, or products with high sugar, fat and salt content. This problem is aggravated in low-income countries where also source data are less available. For aggregate food groups, for which more estimates are available, the researchers still face a difficult choice in choosing between models using different source data, taking different underlying assumptions, and thus applying varied methods and functional forms. In such cases, using meta-estimates combining the findings from available studies could provide more robust estimates. Equally, when estimating elasticities from food expenditure or other consumption data, researchers face similar challenges in choosing the most appropriate data and methods from available alternatives.

The wide range of such alternatives, differing levels of complexity in methods 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 food price elasticity values depending on the methods applied. Few previous studies have attempted to analyse this using the meta-regression approach. Gallet (2009, 2010) analysed variations in the OPEs of meat (Gallet 2010) and fish (Gallet 2009) demand. Chen et al. (2015) analysed both OPEs and CPEs of demand in China for 12 aggregate food groups, alcoholic beverages and tobacco (Chen et al. 2015). All three studies used slightly different explanatory variables in the meta-regression but found significant effects on elasticity estimates from variables describing data type and structure, model structure, model specification, estimation methods and publication type.

In our previous work we conducted a systematic review of literature estimating the demand for foods and beverages and provided meta-estimates for OPEs and CPEs for aggregated food groups in low-, middle- and high-income countries (Green et al. 2013, Cornelsen et al. 2014). In this study we employed the same global database of food price elasticities, extending over 12 years, to investigate and discuss in detail the influence of various methodological aspects on the estimates of both OPEs and CPEs using meta-regression analysis.

It has to be noted that it is particularly important to focus on the impact of the difference in methodological approach on CPE estimates. Changes in own prices have a more noticeable impact on consumption while the marginal impact of price change of a single alternative good is harder to capture. Also, CPEs found in the literature show a high degree of heterogeneity, including switches from positive (substitute goods), to negative (complementary goods). Hence, the bias can potentially cause a change in the direction of the elasticity, but this will be difficult to detect because the sign of the cross-price elasticity cannot be assumed *a priori* for most foods.

## **Methodology**

We used OPE and CPE estimates from a database of food price elasticities compiled from a systematic literature review conducted with an end date in August 2011 for OPEs and in November 2012 for CPEs (both data sets are available upon request from authors) [9,10]. Searches for studies in the review 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 abstracts, estimating food price elasticities of demand using data from 1990 onwards and applying multiple equation methods. It included studies that used nationally representative aggregate data (national average statistics), data from household surveys (cross-sectional) or data from longitudinal surveys. It is important to note that as the criteria prescribed the inclusion of studies employing only post 1990 data, a number of studies employing long time series data, dating back in cases to 1950's, were excluded. While this ignores historic literature, it avoids any systematic differences in elasticities across a long period of time due to vastly changed economic conditions that affect the relationship between food prices and purchasing decisions.

A further distinction in estimated elasticities is between uncompensated (Marshallian) and compensated (Hicksian) elasticities. The latter is of interest when the focus is specifically on price effects net of the income effects. Because of their direct policy relevance, we used only the uncompensated, Marshallian elasticities that combine both price and budget effects. The uncompensated (Marshallian) own- and cross-price elasticities were extracted and aggregated into nine broad categories of food – fruits and vegetables; meat; fish; cereals; dairy; eggs; fats and oils; sweets, confectionery and sweetened beverages (sweets); and other

foods. Price elasticities for food groups at a higher aggregation level than that used in this study (e.g. 'meat and dairy') and cross-price elasticities that, due to aggregation, were within one food group (e.g. cross-price elasticity of pork to beef price) were excluded. Price elasticities that were reported across different sub-population groups were averaged.

The database included also the following information on the included studies: whether the study was published in a peer-reviewed journal, country and region of the study, data source and type and years, function and estimation type in the demand analysis and whether the demand system estimated was complete or conditional. Countries were assigned into low-, middle- and high-income countries following the classification by (Muhammad et al. 2011).

For the purposes of this study additional, more detailed information on data and methods applied in the same set of studies were extracted: data frequency, whether and how censoring in the data was controlled for, which type of data were used for prices, and whether potential biases were addressed in the price data.

#### *Methodological aspects of demand analysis*

There are numerous methods available to estimate the 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 current economic theory on consumer behaviour, 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

beverages) or they can include the whole range of consumer goods, where the former type reflects ‘conditional’ demand and the latter relates to complete demand.

In the analysis we considered following known sources of bias as well as other aspects that may exert a systematic influence on price elasticity estimates:

#### *Different data structures*

The structure of data used to estimate demand systems varies 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 elasticities as cross-sectional data are unable to capture the dynamic components of consumption while time series data can suffer from aggregation bias (Denton and Mountain 2001, Blundell, Pashardes, and Weber 1993). We considered three types of data structure a) aggregate (national average statistics including time series), b) household survey data (cross-sectional) and c) longitudinal survey data (panel). As in individual studies data are often manipulated (e.g. aggregated), we also tested whether the frequency of the time dimension had an impact on the elasticity estimates using three categories of monthly or more frequently, quarterly and annual.

#### *Functional form*

Different functional forms for estimating demand systems can lead to different elasticity estimates (Dameus et al. 2002). The 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), although this linearization has been also associated with potential biases in certain situations (Pashardes 1993). In more recent years



the quadratic version (QAIDS) has become popular, as it allows for a non-linear relationship between income and expenditure across different income groups (Banks, Blundell, and Lewbel 1997). However, other systems are also used, often to address theoretical considerations or specific data issues. For example, the translog model is similar to AIDS but requires a larger data set as the number of parameters to estimate is higher (Barten 1993, Deaton 1986), whereas the LinQuad incomplete demand system is more flexible and imposes fewer restrictions on theoretical consumer preferences in comparison to AIDS (Pan, Mohanty, and Welch 2008). Mixed Demand models assume that for some products the prices are given but for some others it is the quantity that is given and prices adjust to clear the market (e.g. suitable for quickly perishable foods) (Moschini and Rizzi 2005). Endogeneity of quantities, prices and budget can also be accommodated in dynamic demand systems estimated through time series econometric techniques such as cointegrated demand systems (Pesaran and Shin 2002).

#### *Estimation method*

Different estimation methods may also determine elasticity 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 dynamics, habit formation and/or price and/or income expenditure endogeneity by adopting instrumental variable methods, such as two-stage least squares (2SLS) or – more recently – the aforementioned cointegrated demand systems (VEC-AIDS).

#### *Conditionality of the elasticities*

Complete demand systems may be estimated in a single stage, or can be broken down into two or more subsequent stages of budget allocation. For example, Edgerton (Edgerton 1997) assumed a three-step budgeting decision where in the first step the decisions are made on

how much is spent on foods compared to non-food items (health, housing etc). In the second step the budget for foods is divided into 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).

Edgerton (Edgerton 1997) reported that restricting the analysis to the last stage of the multi-stage budgeting process can lead to considerable errors, and suggested correction procedures which are rarely adopted. Rickertsen (Rickertsen 1998) and Klonaris and Hallam (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 and/or short survey period) 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 has been shown to lead to biased estimates of the price elasticities (Heien and Wessells 1990). The most common approach to address the bias is to estimate the demand in two steps (Shonkwiler and Yen 1999) where the first step is the dichotomous decision on whether to consume or not and in the second stage the decision on

how much to consume is taken, or to include a correction term in the demand equations, based on a Heckman-type correction procedure (Heien and Wessells 1990).

#### *Use of unit values as a proxy for price data*

As price data are often missing, particularly in household surveys, unit values, calculated as a ratio of expenditure to its quantity is a common type of price indicator used. This approach offers a solution to missing price data and provides variability in prices that using aggregate consumer or retail prices at one point in time (e.g. cross-sectional data) may not provide (Deaton 1988). 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 data also employed in the model (Deaton 1988). Quality bias can arise because the goods purchased are generally at least to some extent aggregated (e.g. beef rather than specific cuts) and households at higher income levels 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 quality of the foods.

The approaches to adjust for this bias assume that households in the same geographical area and at the same point 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 a more theoretically consistent approach requires the joint estimation of quantity and quality demand functions (Deaton 1988). Because consumers respond to price changes by adjusting their quality allocation, the price variation captured by unit values is usually smaller than the actual one. This means that any consumption response is ascribed to a downward biased estimate of price change, hence generating an overestimate of elasticities.

### *Meta-regression model*

To explore the influence of these methodological approaches separately for OPEs and CPEs we estimated two meta-regression models. To account for study level heterogeneity we estimated a two-level random intercept model where the individual elasticities represented the second level, and study, the first level. The model was fitted using maximum likelihood (ML) with bootstrapped standard errors (50 replications). The dependent variable was the uncompensated OPE or CPE. Independent variables that were used in the model, describing the methodological approaches, are summarised in table 1.

Multicollinearity across the independent variables was tested for using the variance inflation factor (VIF). Variables with VIF values above 10 in the model were removed through testing various model specifications. The best model was chosen based on the highest value for adjusted coefficient of determination ( $R^2$ ) and lowest values for VIF.

Extreme values of elasticities, defined as lying outside of the absolute value of three standard deviations of the mean, within the food group, were considered as outliers. This led to a removal 1.7% (n=47) and 2.41% (n=131) of the observations from OPE and CPE datasets, respectively.

### **Results**

The final database included 130 studies estimating OPEs (n=2,749) and 78 studies reporting CPEs (n=5,191) for any of the nine food groups. The electronic supplement describes each included study in more detail. Table 1 shows the distribution of the variables within the dataset. A large share of OPEs (66%, n=1,803) were from two multi-country studies using International Comparison Program Data (IPCD) (Muhammad et al. 2011, Seale, Regmi, and Bernstein 2003) while CPEs the two largest studies counted only for 28% of observations.

*Table 1 here*

For both OPEs and CPEs, there were more estimates from grey literature, largely conference papers. OPEs were more often estimated for low-income countries while more CPE estimates were available from high-income countries. This is likely due to more detailed data being available from high income countries allowing for more detailed food items to be included. Approximately one third of both OPE and CPE estimates were from Europe.

When the two ICPD studies, estimating unconditional elasticities, were excluded, elasticities were most commonly estimated from complete models (CPE) or conditional on food subgroup expenditure (OPE). Household survey data (cross-sectional) was the most common data structure and annual data frequency was most common for both types of elasticities, even if the ICPD studies were excluded. The majority of elasticities were estimated with a version of the AIDS function if excluding the ICPD studies where the Working Preference Independence (Florida) model was employed. The most common estimation type was SUR if the two big studies were not considered and ML if these were included (OPEs only).

Two-step methods were the most common approach to deal with censored data. For 8% of OPEs (31 studies) and 18% of CPEs (23 studies) it was not reported whether censoring was dealt with (or if it was an issue) but based on the structure of the data used was a possible problem. Also, 46% of OPEs (64 studies) and 40% of CPEs (40 studies) were estimated using unadjusted unit values as approximations for price data, or price data had not been described at all. Lastly, both OPEs and CPEs were mostly estimated for fruits and vegetables or meat and the average data year used in estimation of elasticities was 2000 for OPE's and 2001 for CPE's, respectively.

*Meta-regression results: own-price elasticities*

Table 2 presents the meta-regression results for OPEs. The Likelihood Ratio (LR) test indicated that study level effects were statistically significant ( $p < 0.001$ ) justifying the use of a two-level model. We excluded the variable describing data type as it was leading to multicollinearity in the model and data frequency alone yielded a higher value for adjusted  $R^2$  in comparison to data type. Since OPEs entered the model with their original (negative) sign, a positive coefficient indicates a lower elasticity (i.e. less sensitive demand to changes in prices) and a negative coefficient indicates a higher elasticity (i.e. more sensitive demand to changes in prices).

*Table 2 here*

As expected, OPEs indicated less sensitive demand to price changes as country income level increased with an average difference of 0.27 between the food price elasticity in low-income countries and high-income countries ( $p < 0.001$ ). In comparison to Europe, OPEs from Africa and Asia indicated more sensitive food demand to changes in prices. Differences between Europe and Australasia, North- or South-America were not significant at conventional levels.

Both monthly and quarterly data were associated with higher OPEs (i.e. more sensitive demand to changes in prices) in comparison to annual data ( $p < 0.05$ ). Choice of estimation type was jointly significant ( $p = 0.011$ ) in explaining some of the variation in elasticity estimates although individually only the 'other estimation method' was significantly different (higher elasticity) in comparison to elasticities estimated using SUR method ( $p = 0.001$ ). To the contrary, the type of price data was jointly not significant at conventional levels ( $p = 0.279$ ) although we found OPE estimates from retail price data to be less elastic ( $p = 0.015$ ). This is confirmative evidence that using unadjusted unit prices, as a proxy for retail prices, leads to an overestimation of OPEs in comparison to using actual retail price data.

OPE estimates were also affected by whether or not censoring in the data was addressed. In comparison to two-step methods, aggregating data or using any other method was associated with less elastic OPEs ( $p < 0.001$ ). Equally, when it was not reported how censoring was addressed or where it was not applicable (e.g. aggregate data), the elasticities were associated with less elastic values ( $p < 0.001$ ).

Factors that were not associated with significant changes (at the 5% level) in elasticity estimates were whether the study was peer reviewed, whether elasticities were conditional or unconditional, function type employed and mean year of data.

#### *Meta-regression results: cross-price elasticities*

As the sign of CPE is not predictable, meaning that there is no theoretical prior on 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 table 3, is more complicated and cannot be compared to the *a priori* expectations. Similarly to the OPE model, multicollinearity was detected in the model leading to exclusion of variables describing data type and country income level. Study level effects were equally found to be significant ( $p < 0.001$ ).

CPEs from peer-reviewed studies were weakly associated with more positive values in comparison to grey literature ( $p = 0.063$ ). Regional differences were also detected for CPEs. In comparison to Europe the CPEs were more positive in Asia ( $p < 0.001$ ), North-America ( $p = 0.013$ ) and South-America ( $p = 0.004$ ).

#### *Table 3 here*

Monthly or more frequent data were associated with more positive CPE values ( $p = 0.012$ ) in comparison to annual data, but no significant differences were detected between quarterly or

annual data. LS estimations were associated with smaller elasticities in comparison to models estimated by SUR ( $p=0.017$ ). However, jointly, the estimation type was significant only at the 10% level.

Similarly to the OPEs, the way of addressing censoring in consumption data was found to jointly explain part of the variation in CPEs ( $p<0.001$ ). At the individual level, only studies where censoring was not applicable (e.g. employing aggregate data) were associated with smaller cross-price elasticities ( $p<0.001$ ).

The type of price data used also explained part of the variation in CPEs ( $p<0.001$ ). Adjusted unit prices were associated with more positive cross-price elasticities ( $p<0.001$ ) in comparison to unadjusted unit prices. The coefficient for retail price was also positive but not significant at conventional levels ( $p=0.291$ ). Studies applying other price data (see section 3 for details) were associated with more negative CPE estimates ( $p=0.007$ ). Mean year of data, function type and the conditionality of elasticities, equally to OPEs, were not associated with changes in elasticity estimates at conventional statistical significance levels.

## **Discussion**

There are many individual studies estimating the price sensitivity of food demand across the globe. Only a few have attempted to synthesise this body of research (Andreyeva, Long, and Brownell 2010, Cabrera Escobar et al. 2013, Chen et al. 2015, Cornelsen et al. 2014, Gallet 2010, 2009, Green et al. 2013) and all these analyses have pointed to the wide array of data and methods used in the estimation of price elasticities, which inevitably leads to a question how this affects the sensitivity of the elasticity estimates, particularly when used in policy simulations.



We have added to the literature by using a meta-regression analysis and a large existing data base to examine how methodological differences affect OPE and CPE estimates after controlling for food group, study specific effects, country income level and study region, and whether studies were peer-reviewed. While individual studies in economics have explored the bias in demand analysis of different methodological aspects, the meta-regression analysis approach allowed us to combine these and to explore the influence on the elasticity estimates in a single model.

Similarly to the few previous studies using the same approach (Gallet 2010, 2009, Chen et al. 2015), we found that the different methodological approaches to a smaller or larger extent do matter as these significantly affect food price elasticity estimates. We found statistically significant differences in OPEs estimated using data at different frequencies and estimated by different estimation methods. The latter was also found to be an important influence in the previous two meta-regression analyses of OPEs (for fish and meat only) (Gallet 2010, 2009) and in the analysis of Chinese food price elasticities (Chen et al. 2015).

The method of addressing censoring in the data, led to significant differences in OPE estimates. In particular, using a two-step demand system was associated with smaller (more sensitive) OPEs in comparison to aggregation of data or where no adjustments were done. This finding has relevant implications for future studies as increasingly more disaggregated data is collected and analysed, such as scanner data, which by its nature is highly censored.

For both OPEs and CPEs the type of price data used was associated with significant differences. As the theory predicts, quality adjusted unit values and retail prices led to larger (less sensitive) OPE estimates in comparison to using unadjusted unit values. Hence, attention should be given to which price data are used and whether adjustments for quality differences need to be implemented.

Interestingly, we did not find evidence of significant influence stemming from the choice of functional form or conditionality of the elasticities. However, the functional form was defined only by two categories because the types of models that were non-AIDS were relatively few as by selection criteria only studies using a demand system were included. Similarly, to Chen et al. we found that published papers had significantly more positive CPE's which may indicate some publication bias and certain expectations to the estimated values.

In comparison to OPEs, the impact of methodological bias on CPEs can be more serious as CPEs can switch from negative to positive with a different interpretation for either case (substitute or complement products). CPEs are usually considerably smaller (not far from zero) and thus even small bias can cause the switch in the direction of the effect that in the worst case can lead to a different policy suggestion. This particularly affects studies modelling the potential impact of health- or environment-related food taxes or subsidies where it is necessary to explicitly include cross-price effects to understand the changes across the whole diet, rather than just taxed or subsidised products. If the demand estimation provides inconclusive CPE estimates or estimates that are close to zero, simulation studies should test the sensitivity of their findings by allowing both negative and positive cross-price effects to test the bounds of the outcome measures. Alternatively, meta-estimates, such as provided by (Green et al. 2013, Cornelsen et al. 2014, Gallet 2010, 2009, Andreyeva, Long, and Brownell 2010, Chen et al. 2015, Cabrera Escobar et al. 2013, Clements and Si 2015) should be used.

### **Concluding Comments**

We conclude that studies wishing to employ food price elasticities as parameters in their simulation or other exercises should be careful in choosing these from previous literature or in the choice of methods to be used in the estimation. Where many estimates are available

from previous studies, including measures of precision, researchers should use meta-estimates as these can mitigate some of the bias stemming from methodological differences in individual studies. Where new estimates or single study estimates are used in simulation models, sensitivity of the findings to different values of the elasticities should be tested, particularly for cross-price elasticities.

**Table 1. Description of data**

<b>Variables</b>	<b>OPEs (n=2,749)</b>		<b>CPEs (n=5,191)</b>	
	Obs	%	Obs	%
<i><b>Study peer reviewed?</b></i>				
No	2,196	79.9	3,629	69.9
Yes	553	20.1	1,562	30.1
<i><b>Country Income level</b></i>				
Low	1,148	41.8	1019	19.6
Middle	733	26.7	948	18.3
High	868	31.6	3,224	62.1
<i><b>Region</b></i>				
Africa	598	21.8	388	7.5
Asia	723	26.3	653	12.6
Australasia	58	2.1	161	3.1
Europe	850	30.9	1,560	30.1
North America	302	11.0	1873	36.1
South America	218	7.9	556	10.7
<i><b>Data type</b></i>				
Aggregate	2,002	72.8	185	3.56
Household survey data	569	20.7	4,181	80.5
Longitudinal survey data <sup>a</sup>	178	6.5	825	15.89
<i><b>Data time dimension frequency</b></i>				
Monthly or more frequent	306	11.1	2280	43.9
Quarterly	58	2.1	338	6.5
Annual	2,385	86.8	2,573	49.57

<b><i>Demand system</i></b>				
Complete	1,986	72.2	2181	42.02
Conditional on food group expenditure	383	13.9	2,098	40.02
Conditional on food sub-group expenditure	380	13.8	912	17.57
<b><i>Function type</i></b>				
AIDS	738	26.9	4191	80.7
Non AIDS	2,011	73.2	1000	19.3
<b><i>Estimation type</i></b>				
SUR	372	13.5	2,088	40.2
Least Squares	117	4.3	1,950	37.6
Maximum Likelihood	1,881	68.4	n/a	n/a
Other	97	3.5	231 <sup>b</sup>	4.5
Not reported	282	10.3	922	17.8
<b><i>How censoring in consumption data is managed?</i></b>				
Data aggregated or missing observations replaced by average values	135	4.9	2132	41
Two-step procedure	351	12.8	1,472	28.4
Other <sup>c</sup>	34	1.2	529	10.2
Not reported	232	8.4	911	17.6
Not applicable (e.g. aggregate data)	1,997	72.6	147	2.8
<b><i>Which prices are used?</i></b>				
Retail price or price index	159	5.8	1,542	29.7
Unit price (adjusted to bias)	209	7.6	896	17.3

Unit price (unadjusted to bias)	1,130	41.1	2,092	40.3
Other	1,115	40.6	350	6.7
Not reported	136	5.0	311	6
<b><i>Food Group (price change)</i></b>				
Fruit and vegetables	469	17.1	1,109	21.4
Meat	467	17.0	986	19
Fish	373	13.6	415	8
Dairy	395	14.4	610	11.8
Eggs	17	0.6	174	3.4
Cereals	376	13.7	761	14.7
Fats and oils	305	11.1	289	5.6
Sweets	47	1.7	442	8.5
Other foods	300	10.9	405	7.8
<b><i>Food Group (consumption change)<sup>d</sup></i></b>				
Fruit and vegetables	n/a	n/a	1,140	22
Meat	n/a	n/a	998	19.2
Fish	n/a	n/a	422	8.1
Dairy	n/a	n/a	615	11.9
Eggs	n/a	n/a	179	3.5
Cereals	n/a	n/a	767	14.8
Fats and oils	n/a	n/a	306	5.9
Sweets	n/a	n/a	464	8.9
Other foods	n/a	n/a	300	5.8
<b><i>Mean Year</i></b>	2000		2001	

<sup>a</sup> Studies employing scanner data were assigned one of the categories based on whether any manipulations had been done to the data (e.g. aggregation across time and/or households).

<sup>b</sup> Includes CPEs estimated by ML of which there were too few for a separate category

<sup>c</sup> Mixture of unit price and retail price, self-reported prices, comparative price levels

<sup>d</sup> CPE model only

**Table 2. Meta-regression results for own-price elasticity subsample (n=2,749)**

<b>Variables</b>	<b>Categories</b>	<b>Coef.</b>	<b>p-value</b>
Publication type	Peer-reviewed	-0.004	0.919
Income level	Middle income	0.110	<0.001
	High income	0.273	<0.001
Region	Africa	-0.051	<0.001
	Asia	-0.015	0.009
	Australasia	-0.002	0.905
	North America	-0.007	0.452
	South America	-0.009	0.267
Data frequency	Monthly	-0.253	<0.001
	Quarterly	-0.109	0.037
Demand system	Complete	0.059	0.127
	Conditional on food sub-group expenditure	-0.021	0.660
Function type	Non-AIDS	-0.016	0.853
Estimation type	least squares	-0.098	0.198
	ML	-0.065	0.306
	Other	-0.199	0.001
	not reported	-0.041	0.254
Cons data censoring	Data aggregated/based on average	0.249	<0.001
	Other	0.338	<0.001
	Not reported	0.226	<0.001
	Not applicable	0.320	<0.001
Price type	Retail price	0.093	0.015



	Unit price (adjusted to bias)	0.041	0.321
	Other	0.015	0.745
	Not reported	0.057	0.222
Mean year of data		-0.014	0.114
Constant		28.65	0.129
Food groups		Included	
<b>Random effects parameters</b>			
Study ID	SD(constant)	0.316	
	SD(Residual)	0.250	
LR test vs. linear regression	$\chi^2_{(0,1)} =$	786.0	<0.001

Note: Positive coefficients indicate less sensitive demand to changes in prices and negative coefficients more sensitive demand to changes in prices. Excluded categories: grey literature, low income country, Europe, annual data, conditional on all food expenditure demand system, AIDS or its variant function, SUR estimation, two-step approach to censored data, quality unadjusted unit price data.

**Table 3. Meta-regression results for cross-price elasticity subsample (n=5,191)**

<b>Variables</b>	<b>Category</b>	<b>Coef.</b>	<b><i>p-value</i></b>
Publication type	Peer-reviewed	0.028	0.063
Income level	Middle income	n/a	n/a
	High income	n/a	n/a
Region	Africa	0.048	0.103
	Asia	0.100	<0.001
	Australasia	0.084	0.203
	North America	0.071	0.013
	South America	0.047	0.004
Data frequency	Monthly	0.040	0.012
	Quarterly	0.031	0.612
Demand system	Complete	0.018	0.195
	Conditional on food sub-group expenditure	-0.005	0.779
Function type	Non-AIDS	0.011	0.37
Estimation type	Least squares	-0.042	0.017
	Other (including ML)	-0.018	0.471
	Not reported	-0.026	0.216
Cons data censoring	Data aggregated/based on average	0.006	0.742
	Other	0.010	0.626
	Not reported	0.005	0.749
	Not applicable	-0.113	<0.001

Price type	Retail price	0.023	0.291
	Unit price (adjusted to bias)	0.065	<0.001
	Other	-0.074	0.007
	not described	0.009	0.696
Mean year of data		0.001	0.575
Constant		-0.651	0.893
Food group (price change)		Included	
Food group (consumption change)		Included	
Food group (price change)*food group (consumption change)		Included	
Constant			
<b>Random effects parameters</b>			
Study ID	SD(cons)	0.048	
	SD(Residual)	0.161	
LR test vs. linear regression	$\chi^2_{(0,1)} =$	13.3	<0.001

Note: excluded categories: grey literature, low income country, annual data, conditional on all food expenditure demand system, AIDS or its variant function, SUR estimation, two-step approach to censored data, quality unadjusted unit price data.

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## Appendix 1. Details of included studies

Authors	Year	Country	Data frequency	Data	Function type	Estimation type	Data censoring	Price type	CPE**
Abdulai, A.	2002	Switzerland	Monthly	HH survey	QAIDS	SUR	Not described	Unadj. unit price	y
Ackah, C., Appleton, S.	2011	Ghana	Annual	HH survey	AIDS	SUR	Not described	Other	y
Adam, S. A., Sinne, S.*	2012	Denmark	Monthly	Longitudinal	2-step dynamic censored AIDS	SUR	Two-step method	Unadj. unit price	y
Adhikari, M. et al.	2006	USA	Quarterly	Aggregate	LA-AIDS	SUR	N/A	Not described	y
Agbola, F.W.	2003	South Africa	Annual	HH survey	LA-AIDS	SUR	Not described	Unadj. unit price	
Agbola, F.W. et al.	2003	South Africa	Annual	HH survey	LA-AIDS	SUR	Not described	Unadj. unit price	
Akbay, C. et al	2007	Turkey	Annual	HH survey	LA-AIDS	ITSUR	Two-step method	Unadj. unit price	y
Akinleye, S.O.,Rahij, M.A.Y.	2007	Nigeria	Annual	HH survey	LA-AIDS	SURE	Not described	Unadj. unit price	
Alboghday, M.A., Alashry, M.K.	2010	Egypt	Annual	Aggregate	LA-AIDS	RSUR	N/A	Unadj. unit price	y
Alderman, H.,del Ninno, C.	1999	South Africa	Quarterly	HH survey	AIDS	Not reported	Not described	Unadj. unit price	y
Alfonzo, L., Peterson, H.H.	2006	Paraguay	Annual	HH survey	LA-AIDS	SUR	Two-step method	Qual. adj. unit price	y
Allais, O. et al.	2010	France	Monthly	Longitudinal	AIDS	ITSUR	Aggregate/average	Qual. adj. unit price	y
Allais, O., Nichele, V.	2007	France	Monthly	Longitudinal	MS-AID	BFGS	Aggregate/average	Unadj. unit price	y
Allen, T. et al.	2009	France	Monthly	Longitudinal	LA-AI-HABIT	ITSUR	Aggregate/average	Qual. adj. unit price	y
Al-Shuaiibi, A.	2011	Saudi Arabia	Annual	Aggregate	AIDS	SUR	Not described	Not described	y
Alviola, P., Oral, C.Jr.	2010	USA	Annual	HH survey	Heckman two-step model	OLS	Two-step method	Unadj. unit price	
Angulo, A.M. et al.	2003	Spain	Annual	Longitudinal	GADS	FIML	Aggregate/average	Qual. adj. unit price	y
Angulo, A.M., Gil, J.M.	2006	Spain	Annual	Longitudinal	AIDS	ITIP	Other	Qual. adj. unit price	y



Authors	Year	Country	Data frequency	Data	Function type	Estimation type	Data censoring	Price type	CPE**
Angulo, A.M.et al.	2002	Spain	Quarterly	Longitudinal	Rotterdam model	SUR-GLS	Not described	Qual. adj. unit price	
Anwar, A. et al.*	2012	Pakistan	Annual	HH survey	Rotterdam	SUR	Not described	Unadj. unit price	y
Balcombe, K. et al.	1999	Bulgaria	Monthly	HH survey	AIDS	Empirical Bayesian	N/A	Unadj. unit price	y
Beach, R.H., Zhen, C.	2009	Italy	Monthly	Aggregate	SNAP AIDS	GMM	N/A	Unadj. unit price	
Berges, M.E., Casellas, K.S	2002	Argentina	Annual	HH survey	Linear Expenditure System	SUR	Two-step method	Qual. adj. unit price	
Bouamra Mechemache Z. et al.	2008	Italy	Monthly	Longitudinal	LA-AI	ML	Not described	Retail price	y
Boysen, O.*	2012	Uganda	Annual	HH survey	QUAIDS	Iterative LS	Two-step method	Qual. adj. unit price	y
Brosig, S.	2000	Hungary	Annual	HH survey	LA-AIDS	SUR	Two-step method	Qual. adj. unit price	y
Brown, M. G., Jauregui, C.E.*	2011	US	Monthly	Aggregate	Rotterdam model	SUR	Not described	Unadj. unit price	y
Bunte, F., Vavra, P.	2006	Netherlands	Monthly	Aggregate	AIDS	SUR	N/A	Retail price	
Cakir, M., Balagtas, J.V.	2010	USA	Quarterly	Aggregate	LA-AIDS	SUR	N/A	Retail price	
Capacci, S., Mazzocchi, M.	2011	UK	Annual	HH survey	QAIDS	FIML	Two-step method	Qual. adj. unit price	
Caracciolo, F., Cembalo, L.	2010	Italy	Monthly	Longitudinal	LA-AIDS	Not reported	Two-step method	Unadj. unit price	
Castellon, C.E.*	2012	Ecuador	Annual	HH survey	AIDS	ITSUR	Two-step method	Qual. adj. unit price	y
Castellon, CE., et al.*	2012	US	Annual	HH survey	LA/EASI	SUR	Two-step method	Retail price	y
Coelho, A.B., et al.	2010	Brazil	Annual	HH survey	QAIDS	ML, nonlinear SUR	Two-step method	Unadj. unit price	y
Coffey, B. et al.*	2010	US	Monthly	Longitudinal	AIDS	EM	Other	Retail price	y
Conte, A.	2006	Egypt	Annual	HH survey	AIDS	SURE	Aggregate/average	Qual. adj. unit price	y
Davis, C.G. et al.	2008	USA	Annual	HH survey	Censored translog demand system	ML,ITSUR	Two-step method	Unadj. unit price	y

Authors	Year	Country	Data frequency	Data	Function type	Estimation type	Data censoring	Price type	CPE**
Davis, C.G., et al	2011	USA	Monthly	Longitudinal	Censored AIDS	BH	Two-step method	Not described	
Davis, C.G., et al.	2007	USA	Annual	HH survey	Censored translog demand system	ML,ITSUR	Two-step method	Unadj. unit price	y
Davis, C.G., et al.	2009	USA	Monthly	Longitudinal	Censored translog demand system	ML,ITSUR	Two-step method	Not described	
Dey, M.M. et al.	2008	Multiple	Annual	HH survey	QAIDS	Not reported	Two-step method	Not described	
Dharmasena, S., Capps, O.J.	2011	USA	Monthly	Aggregate	LA/QUAIDS	Not reported	Aggregate/average	Other	y
Di Giusepp, S.*	2011	Paraguay	Annual	HH survey	LinQuad incompleted demand system	Not reported	Not described	Qual. adj. unit price	y
Dong, D. et al.	2007	Norway	Monthly	Longitudinal	LA-AIDS	ML	Other	Qual. adj. unit price	y
Ecker, O., Qaim, M.	2011	Malawi	Annual	HH survey	QAIDS	Not reported	Two-step method	Qual. adj. unit price	
Elsner, K.	1999	Russia	Annual	HH survey	LA-AIDS	Non-linear LS	Two-step method	Qual. adj. unit price	
Erjavec, E., et al.	1998	Slovenia	Annual	HH survey	LA-AIDS	SURE	Not described	Qual. adj. unit price	
Fabiosa, J.F.	2006	Indonesia	Annual	HH survey	Double-hurdle	Likelihood fn	Two-step method	Retail price	
Fabiosa, J.F., Jensen, H.H.	2002	Indonesia	Annual	HH survey	LA-AIDS	Not reported	Two-step method	Not described	y
Fabiosa, J.F., Jensen, H.H.	2003	Indonesia	Annual	HH survey	LinQuad incomplete demand system	Not reported	Other	Not described	y
Fousekis, P., Revell, B.J.	2004	UK	Monthly	Longitudinal	Nonlinear AIDS	Not reported	N/A	Unadj. unit price	
Frohberg, K., Winter, E.	2001	Lithuania	Annual	HH survey	NQ-QES	Not reported	Not described	Not described	y
Garcia Y.T., et al.	2005	Philippines	Annual	HH survey	QAIDS	Not reported	Two-step method	Retail price	
Gibson, J., Rozele, S.	2002	Papua New Guinea	Annual	HH survey	Share-log (Deaton)	Not reported	Not described	Retail price	
Golan, A., et al.	2001	Mexico	Annual	HH survey	AIDS	GME	Other	Other	
Gould, B.W.	1996	USA	Monthly	Longitudinal	Censored demand model	ML	Two-step method	Unadj. unit price	

Authors	Year	Country	Data frequency	Data	Function type	Estimation type	Data censoring	Price type	CPE**
Griffith, R. et al.*	2012	UK	Monthly	Longitudinal	QUAIDS	GMM	Aggregate/average	Unadj. unit price	y
Guadalupe, B-R.J. et al.	2010	Mexico	Monthly	Aggregate	Simultaneous equation system	2SLS	N/A	Retail price	
Gulseven, O., Wohlegant, M.	2010	USA	Monthly	Aggregate	Rotterdam model	Not reported	N/A	Other	
Gustavsen, G.W., Rickertsen, K.	2003	Norway	Quarterly	Aggregate	AIDS	Not reported	N/A	Retail price	y
Härkänen, T. et al.*	2011	Finland	Annual	HH survey	QAIDS	3SLS	Not described	Retail price	y
Hassan, A.R.	2012	Columbia	Quarterly	Aggregate	Error Correction Linear AIDS	Not reported	N/A	Other	
Hoang, L.V.	2009	Vietnam	Annual	HH survey	LA-AIDS	Not reported	N/A	Qual. adj. unit price	y
Hoderlain, S., Mihaleva, S.	2008	UK	Annual	HH survey	AIDS	3SLS/GMM	Not described	Other	
Hossain, F., et al.	2001	Latvia	Monthly	HH survey	AIDS	SUR	Not described	Retail price	y
Hossain, F., Jensen, H.H.	2000	Lithuania	Monthly	Longitudinal	LA-AIDS	OLS	Aggregate/average	Qual. adj. unit price	y
Huang, S-J., Show, C.-R.	2010	Taiwan	Monthly	Aggregate	AIDS	iterative 3SLS	N/A	Other	y
Huq, A.S.M.A., et al.	2004	Bangladesh	Annual	HH survey	LA-AIDS	Not reported	Not described	Unadj. unit price	y
Hutasuhut, M. et al.	2001	Indonesia	Annual	HH survey	LA-AIDS	Not reported	Two-step method	Not described	
Ishdorj, A., Jensen, H.H.	2008	USA	Monthly	Longitudinal	Censored AIDS	Bayesian	Other	Unadj. unit price	
Islam, M.R. et al.	2007	Bangladesh	Annual	HH survey	LA-AIDS	OLS	Not described	Unadj. unit price	y
Ismail, S.Z., Lofti, G.R.	2007	Egypt	Annual	Aggregate	Barton mixed model/AIDS	Not reported	Not described	Not described	y
Jabarin, A.S., Al-Karablieh, E.K.	2011	Jordan	Annual	HH survey	LA-AIDS	ITSUR	Two-step method	Not described	
Jaffry, S., Brown, J.	2008	UK	Monthly	Aggregate	Dynamic AIDS	Not reported	N/A	Unadj. unit price	
Klonaris, S., Karagiannis, G.	2002	Greece	Annual	HH survey	LA-AIDS	Not reported	Two-step method	Qual. adj. unit price	

Authors	Year	Country	Data frequency	Data	Function type	Estimation type	Data censoring	Price type	CPE**
Kuchler, F. et al.	2010	USA	Monthly	Aggregate	LA-AIDS	ISUR	N/A	Unadj. unit price	
Kumar, P., Dey, M.M.	2004	Canada/ India	Annual	HH survey	QAIDS	Not reported	Aggregate/average	Other	
Lazaridis, P.	2003	Greece	Annual	HH survey	LA-AIDS	SURE	Two-step method	Qual. adj. unit price	
Le, C.Q.	2008	Vietnam	Annual	HH survey	AIDS	OLS	Not described	Retail price	
Lecocq, S., Robin, J.-M.	2006	France	Quarterly	Longitudinal	QAIDS	ITSUR	Aggregate/average	Unadj. unit price	
Leffler, K.K. et al.*	2012	US	Annual	HH survey	EASI	SUR	Aggregate/average	Qual. adj. unit price	y
Lema, D., et al.	2007	Paraguay/ Bolivia	Annual	HH survey	LinQuad	ISUR	Two-step method	Unadj. unit price	y
Lin, B.H., et al.	2008	USA	Annual	HH survey	Translog model	Not reported	Two-step method	Unadj. unit price	
Lin, B.H., et al.	2011	USA	Monthly	Aggregate	AIDS	ITSUR	N/A	Unadj. unit price	y
Llanto, G.M.	1996	Philippines	Annual	HH survey	QAIDS	ITSSUR	Not described	Not described	y
Lopez, J.A, Malaga, J. E.	2009	Mexico	Annual	HH survey	Two-step censored demand model	ML	Two-step method	Unadj. unit price	y
Luchini, S. R., et al.	2001	Bulgaria	Monthly	Aggregate	AIDS	SUR	N/A	Not described	y
Ma, H. et al.	2003	China	Annual	Aggregate	LA-AIDS	ITSUR	N/A	Other	
Maynard, L.J.	2000	USA	Monthly	Aggregate	LA-AIDS	ITSUR	N/A	Retail price	
Maynard, L.J., Liu, D.	1999	USA	Monthly	Aggregate	LA-AIDS	Not reported	N/A	Unadj. unit price	
Mazzocchi, M.	2004	Italy	Monthly	Aggregate	AIDS	SUR	Aggregate/average	Retail price	y
Meyerhoefer, C.D., et al.	2005	Romania	Monthly	Longitudinal	Continuous/censored commodity demand system	GMM	Other	Qual. adj. unit price	y
Minot, N., Goletti, F.	2000	Vietnam	Annual	HH survey	LA-AIDS	Not reported	Not described	Other	
Monnet Benoit, P.G., Souza-Posa, A.	2011	Cote d'Ivoire	Annual	HH survey	LA-AIDS	2SLS	Aggregate/average	Qual. adj. unit price	y
Moschini, G., Rizzi, P.L.	2007	Italy	Monthly	Aggregate	NQ Mixed Demand System	ML	N/A	Qual. adj. unit price	

Authors	Year	Country	Data frequency	Data	Function type	Estimation type	Data censoring	Price type	CPE**
Moschini, G., Rizzi, PL.	2005	Italy	Monthly	Aggregate	Stone-Geary Mixed Demand Model	ML	N/A	Qual. adj. unit price	
Mudassar, K. et al.*	2012	Pakistan	Annual	HH survey	LA/AIDS	ITSUR	Not described	Unadj. unit price	y
Muhammad, A., et al.	2011	Multiple	Annual	Aggregate	Florida-Slutsky	ML	N/A	Other	
Mutondo, J.E, Henneberry, S.R.	2007	USA	Quarterly	Aggregate	Rotterdam model	ITSUR	N/A	Unadj. unit price	
Niimi, Y.	2005	Vietnam	Annual	HH survey	LA-AIDS	SUR	Not described	Retail price	
Okrent, A.M., Alston, J.M.	2011	USA	Monthly	Aggregate	FD-LAIDS	ITSUR	Aggregate/average	Retail price	y
Okrent, A.M., Alston, J.M.*	2012	USA	Monthly	HH Survey	GODDS	GLS	Aggregate/average	Retail price	y
Ozer, H.	2003	Turkey	Annual	HH survey	Linear Expenditure System	SUR	Not described	Retail price	y
Peterson, H.H., Chen Y.	2005	Japan	Monthly	Aggregate	Rotterdam model	Not reported	N/A	Retail price	y
Piggot, N.E., et al.	2007	USA	Monthly	Aggregate	Generalized AIDS	ITSUR	N/A	Unadj. unit price	
Pintos-Payeras, J.A.	2009	Brazil	Annual	HH survey	AIDS	Not reported	Not described	Retail price	y
Pittman, G.F.	2004	USA	Annual	HH survey	LA-AIDS	SUR	Two-step method	Unadj. unit price	y
Pofahl, G.M., et al.	2005	USA	Annual	HH survey	QAIDS	ITSUR	N/A	Unadj. unit price	y
Pomboza, R. Mbaga, M.	2007	Canada	Annual	HH survey	AIDS	SUR	Aggregate/average	Unadj. unit price	y
Pruitt, J.R., Raper, K.C.	2010	USA	Monthly	Aggregate	AIDS	GMM	Not described	Retail price	
Quagraine, K.	2003	USA	Monthly	Aggregate	Dynamic AIDS	Non-linear procedure in SHAZAM	N/A	Other	
Radwan, A. et al.	2009	Spain	Monthly	Aggregate	Generalized AIDS	Not reported	N/A	Retail price	
Radwan, A., et al.	2008	Spain	Monthly	Aggregate	Generalized AIDS	Largest likelihood function value	N/A	Retail price	
Ragab, M.A.S., et al.	2008	Egypt	Annual	Aggregate	LA-AIDS	3SLS	Not described	Not described	y

<b>Authors</b>	<b>Year</b>	<b>Country</b>	<b>Data frequency</b>	<b>Data</b>	<b>Function type</b>	<b>Estimation type</b>	<b>Data censoring</b>	<b>Price type</b>	<b>CPE**</b>
Ramadan, R., Thomas, A.	2011	Egypt	Annual	Aggregate	Mixed demand model	Non-linear SUR	Aggregate/average	Other	y
Raper, K.C.	2002	USA	Annual	HH survey	Linear Expenditure System	Non-linear SUR	Two-step method	Retail price	
Razzaque, A. et al.	1997	Bangladesh	Annual	HH survey	Food Characteristics Demand System (FCDS)	Not reported	Not described	Other	y
Regorsek, D., Erjavec, E.	2007	Slovenia	Annual	HH survey	LA-AIDS	System linear regression	Aggregate/average	Unadj. unit price	
Revoredo-Giha, C., et al.	2009	Scotland	Monthly	Aggregate	LA-AIDS	SURE	N/A	Unadj. unit price	
Rickertsen, K., Kristofersson, D.	2003	Norway	Annual	Aggregate	LA-AIDS	3SLS	N/A	Other	
Rickertsen, K.	1998	Norway	Annual	Aggregate	AIDS	SUR	N/A	Other	
Santarossa, J.M, Mainland, D.D.	2003	UK	Monthly	Longitudinal	AIDS	Not reported	Aggregate/average	Unadj. unit price	y
Schmit, T.M, et al.	2002	USA	Monthly	Longitudinal	Two-step censored demand model	ML	Two-step method	Unadj. unit price	
Sckokai, P, et al.	2009	Italy	Monthly	Aggregate	AIDS	GMM	Aggregate/average	Unadj. unit price	
Seale, J., et al.	2003	Multiple	Annual	Aggregate	Florida-Slutsky	ML	N/A	Unadj. unit price	
Shirota, R., Sonoda, D.Y.*	2012	Brazil	Annual	HH survey	AIDS	GLS	Not described	Not described	y
Smed, S., et al.	2007	Denmark	Monthly	Aggregate	AIDS	ML	Aggregate/average	Unadj. unit price	
Souza, G.S., et al.	2008	Brazil	Annual	Aggregate	Partial Equilibrium Model	3SLS	N/A	Other	
Stockton, C., Capps, O.	2005	USA	Annual	HH survey	Censored AIDS	OLS	Two-step method	Unadj. unit price	y
Taniguchi, K., Chern, W.S	2000	Japan	Monthly	HH survey	AIDS	ITSUR	Two-step method	Other	y
Tekguc, H.*	2011	Turkey	Annual	HH survey	LA/AIDS	FGLS	Two-step method	Not described	y
Tey, S.Y., et al.	2008	Malaysia	Annual	HH survey	LA-AIDS	Not reported	Not described	Not described	
Tey, S.Y., et al.	2008	Malaysia	Annual	HH survey	LA-AIDS	ML	Two-step method	Not described	

Authors	Year	Country	Data frequency	Data	Function type	Estimation type	Data censoring	Price type	CPE**
Thiele, S.	2008	Germany	Annual	HH survey	LA-AIDS	SUR	Two-step method	Qual. adj. unit price	
Thiele, S.	2010	Germany	Annual	HH survey	LA-AIDS	SUR	Two-step method	Qual. adj. unit price	y
Tiffin, R. et al.*	2011	UK	Annual	HH survey	AIDS	SUR	Other	Unadj. unit price	y
Tiffin, R., Arnoult, M.	2010	UK	Annual	HH survey	AIDS	Bayesian	Other	Unadj. unit price	y
Tinooco, J.R., et al.	2011	Mexico	Monthly	Aggregate	AIDS	SUR (SYSLIN/SUR)	N/A	Retail price	y
Turk, J., Erjavec, E.	2001	Slovenia	Annual	HH survey	LA-AIDS	SURE	Not described	Unadj. unit price	y
ul Haq, Z. et al.	2008	Pakistan	Annual	HH survey	LA-AIDS	ITSUR	Not described	Not described	
Ulimwengu, J.M. et al.	2009	Ethiopia	Annual	HH survey	AIDS	SUR	Not described	Not described	y
Ulimwengu, J.M., Ramadan, R.	2009	Uganda	Annual	HH survey	AIDS	Not reported	Not described	Not described	
Ulubasoglu, M. et al.	2010	Australia	Quarterly	HH survey	LA-AIDS	Not reported	Two-step method	Retail price	y
Verbeke, W., Ward, R. W.	2001	Belgium	Monthly	Longitudinal	AIDS	Not reported	N/A	Not described	
Weliwita, A., et al.	2003	Tanzania	Annual	HH survey	LA-AIDS	Nonlinear ITSUR	Two-step method	Unadj. unit price	y
Yeboah, G., Maynard, L.J.	2004	Japan	Monthly	Aggregate	Rotterdam model	SUR	N/A	Retail price	y

\*only cross-price elasticities are extracted from these studies as search for publications estimating cross-price elasticities was done separately and with a later end date. While own-price elasticity estimates are available from these studies, these are not included to avoid bias as this would exclude studies not presenting cross-price elasticities and dating beyond August 2011.

\*\*Studies present cross-price elasticities

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