Applied Economic Perspectives and Policy Advance Access published May 20, 2016
Applied Economic Perspectives and Policy (2016) volume 0, number 0, pp. 1–16.
doi:10.1093/aepp/ppw010

Submitted Article

Estimating the Relationship between Food Prices and Food Consumption—Methods Matter

Laura Cornelsen*, Mario Mazzocchi, Rosemary Green,
Alan D. Dangour, and Richard D. Smith

Laura Cornelsen is a lecturer in health economics at the London School of Hygiene and Tropical Medicine, Mario Mazzocchi is an associate professor at the University of Bologna. Rosemary Green is a lecturer in nutrition and sustainability at the London School of Hygiene and Tropical Medicine. Alan D. Dangour is a reader at the London School of Hygiene and Tropical Medicine, Richard D. Smith is a professor of health systems economics at the London School of Hygiene and Tropical Medicine.
*Correspondence may be sent to: laura.cornelsen@lshtm.ac.uk.

Submitted 6 February 2015; accepted 24 March 2016.

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 used 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.*

Key words: food demand, method, own-price elasticity, cross-price elasticity, meta-regression

JEL codes: D11, H31, Q18.

Downloaded from http://aepp.oxfordjournals.org/ at University of Wollongong on May 23, 2016

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 the rising prevalence of obesity and non-communicable disease globally (Tiffin and Arnoult 2011; Briggs et al. 2013; Basu et al. 2014; Manyema et al. 2014; Leifert and Lucina 2015; NiMhurchu et al. 2015; 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

The Author 2016. Published by Oxford University Press on behalf of the Agricultural and Applied Economics Association. All rights reserved. For permissions, please e-mail: journals.permissions@oup.com

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 (Wirsenius, Hedenus, and Mohlin 2011; Green et al. 2015; Säll and Gren 2015; Briggs et al. 2016). To evaluate the effectiveness of this type of policy 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 (OPEs and CPEs), both of which 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 their consumption by 5.6%, but also resulted in a 3% increase in the consumption of cereal, dairy, and fruits and vegetables, thus offsetting 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 their 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 the unexpected effect of increasing the total calories consumed via substitution to relatively cheaper and staple foods (Cornelsen et al. 2014).

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 less evidence available on detailed food items that might be of interest in the context of a specific policy (e.g. sugar-sweetened beverages or diet beverages) (Andreyeva et al. 2010, Green et al. 2013). This problem is aggravated in low-income countries where source data are also less available. For aggregate food groups, for which more estimates are available, the researchers still face a difficult choice in choosing between studies 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 (Cox and Wohlgenant 1986; Deaton 1988; Shonkwiler and Yen 1999)

Downloaded from http://aepp.oxfordjournals.org/ at University of Wollongong on May 23, 2016

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 analyze this using the meta-regression approach. Gallet (2009, 2010) analyzed variations in the OPEs of meat (Gallet 2010) and fish (Gallet 2009) demand. Chen et al. (2015) analyzed both OPEs and CPEs of demand in China for 12 aggregate food groups, alcoholic beverages, and tobacco (Chen et al. 2015). All three studies have 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 whether studies have been published in an academic journal.

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 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 differences 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 CPE 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 the authors). 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 Google Scholar, Ideas, Eldis, as well as websites from the USDA, the Food and Agricultural Organization of the United Nations, The World Bank, and the International Food Policy Research Institute).

The review included published and grey literature, with English abstracts, estimating food price elasticities of demand using data from 1990 onward and applying multiple equation methods. The included studies used a range of different types of data, for example, 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 lenghty time series data, in some cases dating back to the 1950s, 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.

Downloaded from http://aepp.oxfordjournals.org/ at University of Wollongong on May 23, 2016

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 also covered 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 that researchers are willing to make, as well as on data availability. The systematic review described above, and this article, focuses on research employing multiple equation methods for demand analysis, in coherence with current economic theory on consumer behavior, 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 since 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 a number of known sources of bias (described below) 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

Downloaded from http://aepp.oxfordjournals.org/ at University of Wollongong on May 23, 2016

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 because cross-sectional data are unable to capture the dynamic components of consumption, while time series data can suffer from aggregation bias (Blundell, Pashardes, and Weber 1993; Denton and Mountain 2001). 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 the data in individual studies 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: 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 also been 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 (Deaton 1986; Barten 1993), 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

Downloaded from http://aepp.oxfordjournals.org/ at University of Wollongong on May 23, 2016

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 the 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 that 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 and/or short survey period), or non-consumption explained by price and income level (i.e., at a different price/income level that 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 value, calculated as a ratio of expenditure to its quantity, is a commonly used type of price indicator. 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.

Downloaded from http://aepp.oxfordjournals.org/ at University of Wollongong on May 23, 2016

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 represented 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 to describe the methodological approaches are summarized 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 of the observations from OPE and CPE datasets of 1.7% (n = 47) and 2.41% (n = 131), 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; Seale, Regmi, and Bernstein 2003; Muhammad et al. 2011) while CPEs in the two largest studies counted only for 28% of observations.

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, thus 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 sub-group expenditure (OPE). Household

Downloaded from http://aepp.oxfordjournals.org/ at University of Wollongong on May 23, 2016

Table 1 Description of Data

Variables	OPEs (n = 2,749) Obs.	%	CPEs (n = 5,191) Obs.	%
Study peer reviewed?				
No	2,196	79.9	3,629	69.9
Yes	553	20.1	1,562	30.1
Country Income level				
Low	1,148	41.8	1019	19.6
Middle	733	26.7	948	18.3
High	868	31.6	3,224	62.1
Region				
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
Data type				
Aggregate	2,002	72.8	185	3.56
Household survey data	569	20.7	4,181	80.5
Longitudinal survey data[a]	178	6.5	825	15.89
Data time dimension frequency				
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
Demand system				
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
Function type				
AIDS	738	26.9	4191	80.7
Non AIDS	2,011	73.2	1000	19.3
Estimation type				
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[b]	4.5
Not reported	282	10.3	922	17.8
How is censoring in consumption data managed?				
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	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
Which prices are used?				
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[c]	1,115	40.6	350	6.7
Not reported	136	5.0	311	6

Continued

Downloaded from http://aepp.oxfordjournals.org/ at University of Wollongong on May 23, 2016

Table 1 *Continued*

Variables	OPEs (n = 2,749) Obs.	%	CPEs (n = 5,191) Obs.	%
Food Group (price change)				
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
Food Group (consumption change)[d]				
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
Mean Year	2000		2001	

Note: Superscript [a] indicates that 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); superscript [b] indicates that this value includes CPEs estimated by ML, of which there were too few for a separate category; superscript [c] indicates a mixture of unit price and retail price, self-reported prices, comparative price levels; superscript [d] indicates a CPE model only.

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 the estimation of elasticities was 2000 for OPEs and 2001 for CPEs, 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

Downloaded from http://aepp.oxfordjournals.org/ at University of Wollongong on May 23, 2016

Table 2 Meta-regression Results for Own-price Elasticity Subsample ($n = 2{,}749$)

Variables	**Categories**	**Coef.**	***p*-value**
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	
Random effects parameters			
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 indicate more sensitive demand to changes in prices. Excluded categories are as follows: 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, and quality unadjusted unit price data.

(p<0.001), thus 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).

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

Downloaded from http://aepp.oxfordjournals.org/ at University of Wollongong on May 23, 2016

Europe and Australasia, or North America 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 the 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 on food group or overall food expenditure, 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 the 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 ($p=0.004$).

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

Downloaded from http://aepp.oxfordjournals.org/ at University of Wollongong on May 23, 2016

Table 3. Meta-regression Results for Cross-price Elasticity Subsample (n=5,191)

Variables	**Category**	***Coef.***	***p*-value**
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			
Random effects parameters			
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 are as follows: 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, and quality unadjusted unit price data.

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 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

Many individual studies estimate the price sensitivity of food demand across the globe. Only a few, have attempted to synthesize this body of

Downloaded from http://aepp.oxfordjournals.org/ at University of Wollongong on May 23, 2016

research (Gallet 2009, 2010; Andreyeva, Long, and Brownell 2010; Cabrera Escobar et al. 2013; Green et al. 2013; Cornelsen et al. 2014; Chen et al. 2015) 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 2009, 2010; 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 2009, 2010) 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 the 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 analyzed, 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 because by selection criteria only studies using a demand system were included. Similar to Chen et al. we found that published papers had more positive CPEs, 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 a 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 modeling the potential impact of health- or environment-related food taxes or subsidies, where it is necessary to explicitly include cross-price effects to

Downloaded from http://aepp.oxfordjournals.org/ at University of Wollongong on May 23, 2016

understand the changes across the whole diet, rather than just taxed or subsidized 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 those provided by (Gallet 2009, 2010; Andreyeva, Long, and Brownell 2010; Cabrera Escobar et al. 2013; Green et al. 2013; Cornelsen et al. 2014; Chen et al. 2015; and Clements and Si 2015) should be used.

Conclusions

We conclude that studies wishing to employ food price elasticities as parameters in their simulation or other exercises should be careful when choosing these from previous literature, or when choosing 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.

Funding

This work has been partly supported by the Leverhulme Centre for Integrative Research on Agriculture and Health (LCIRAH).

References

Andreyeva, T., M.W. Long, and K.D. Brownell. 2010. The Impact of Food Prices on Consumption: A Systematic Review of Research on the Price Elasticity of Demand for Food *American Journal of Public Health* 100 (2): 216–22.

Banks, J., R. Blundell, and A. Lewbel. 1997. Quadratic Engel Curves and Consumer Demand. *Review of Economics and Statistics* 79: 527–39.

Barten, A.P. 1993. Consumer Allocation Models: Choice of Functional Form. *Empirical Economics* 18: 129–58.

Basu, S., S. Vellakkal, S. Agrawal, D. Stuckler, B. Popkin, and S. Ebrahim. 2014. Averting Obesity and Type 2 Diabetes in India through Sugar-Sweetened Beverage Taxation: An Economic-Epidemiologic Modeling Study. *Plos Medicine* 11 (1):1–13.

Blundell, R., P. Pashardes, and G. Weber. 1993. What Do We Learn about Consumer Demand Patterns from Micro Data? *American Economic Review* 83 (3): 570–97.

Briggs, A.D.M., A. Kehlbacher, R. Tiffin, and P. Scarborough. 2016. Simulating the Impact on Health of Internalising the Cost of Carbon in Food Prices Combined with a Tax on Sugarsweetened Beverages. *BMC Public Health* 16 (107): 1–14.

Briggs, A.D.M., O.T. Mytton, A. Kehlbacher, R. Tiffin, M. Rayner, and P. Scarborough. 2013. Overall and Income Specific Effect on Prevalence of Overweight and Obesity of 20% Sugar Sweetened Drink Tax in UK: Econometric and Comparative Risk Assessment Modelling Study. *BMJ* 347:f6189.

Cabrera Escobar, M.A., J.L. Veerman, S.M. Tollman, M.Y. Bertram, and K.J. Hofman. 2013. Evidence that a Tax on Sugar Sweetened Beverages Reduces the Obesity Rate: A Meta-analysis. *BMC Public Health* 13 (1072):DOI: 10.1186/1471-2458-13-1072.

Downloaded from http://aepp.oxfordjournals.org/ at University of Wollongong on May 23, 2016

Chen, D, D Abler, D Zhou, X Yu, and W Thompson. 2015. A Meta-analysis of Food Demand Elasticities for China. *Applied Economic Perspectives and Policy* doi:10.1093/aepp/ppv006.

Clements, K.W., and J. Si. 2015. Price Elasticities of Food Demand: Compensated vs. Uncompensated. *Health Economics* DOI: 10.1002/hec.3226.

Cornelsen, L., R. Green, A.D. Dangour, R. Turner, B. Shankar, M. Mazzocchi, and R.D. Smith. 2014. What Happens to the Pattern of Food Consumption when Food Prices Change? Evidence from a Systematic Review and Meta-analysis of Food Cross-price Elasticities Globally. *Health Economics* 24 (12):1548–59.

Cox, T., and M. Wohlgenant. 1986. Prices and Quality Effects in Cross-sectional Demand Analysis. *American Journal of Agricultural Economics* 68: 908–19.

Dameus, A., F.G.C. Richter, B.W. Brorsen, and K.P. Sukhudail. 2002. AIDS versus the Rotterdam Demand System: A Cox Test with Parametric Bootstrap. *Journal of Agricultural and Resource Economics* 27 (2): 335–47.

Deaton, A. 1988. Quality, Quantity and Spatial Variation of Price. *American Economic Review* 78: 418–30.

——. 1986. Demand Analysis. In *Handbook of Econometrics*, ed. Z. Griliches and M.D. Intriligator, 1768–1839. Amsterdam: Elsevier.

Deaton, A., and M. Grosh. 2000. Consumption. In *Designing Household Survey Questionnaires for Developing Countries: Lessons from Ten Years of LSMS Experience*, ed. by M. Grosh and P. Glewwe, 91–133. Washington DC: World Bank.

Deaton, A., and J. Muellbauer. 1980. An Almost Ideal Demand System. *American Economic Review* 70: 312–26.

Denton, F.T., and D.C. Mountain. 2001. Income Distribution and Aggregation/disaggregation Biases in the Measurement of Consumer Demand Elasticities. *Economics Letters* 73 (1): 21–8.

Edgerton, D.L. 1997. Weak Separability and the Estimation of Elasticities in Multistage Demand System. *American Journal of Agricultural Economics* 79 (1): 62–79.

Gallet, C.A. 2009. The Demand for Fish: A Meta-analysis of the Own-Price Elasticity. *Aquaculture Economics and Management* 13 (3): 235–45.

——. 2010. Meat Meets Meta: A Quantitative Review of the Price Elasticity of Meat. *American Journal of Agricultural Economics* 92 (1): 258–72.

Green, R., J. Milner, A.D. Dangour, A. Haines, Z. Chalabi, A. Markandya, J. Spadaro, and P. Wilkinson. 2015. The Potential to Reduce Greenhouse Gas Emissions in the UK through Healthy and Realistic Dietary Change. *Climatic Change* 129: 253–65.

Green, R., L. Cornelsen, A.D. Dangour, R. Turner, B. Shankar, M. Mazzocchi, and R.D. Smith. 2013. The Effect of Rising Food Prices on Food Consumption: Systematic Review with Meta-regression. *BMJ* 346: f3703.

Heien, D.M., and C.R. Wessells. 1990. Demand Systems Estimation with Microdata: A Censored Regression Approach. *Journal of Business, Economics and Statistics* 8 (3): 365–71.

Klonaris, S., and D. Hallam. 2003. Conditional and Unconditional Food Demand Elasticities in A Dynamic Multistage Demand System. *Applied Economics* 35 (5): 503–14.

Leifert, R.M., and C.R. Lucina. 2015. Linear Symmetric Fat Taxes: Evidence from Brazil. *Applied Economic Perspectives and Policy* doi: 10.1093/aepp/ppu062.

Manyema, M., L.J. Veerman, L. Chola, A. Tugendhaft, B. Sartorius, D. Labadarios, and K.J. Hofman 2014. The Potential Impact of a 20% Tax on Sugar-Sweetened Beverages on Obesity in South African Adults: A Mathematical Model. *PloS ONE* 9 (8):e105287.

Moschini, G.C., and P.L. Rizzi. 2005. Coherent Specification of a Mixed Demand System: The Stone-Geary Model. In *Exploring Frontiers in Applied Economics: Essays in honor of Stanley R. Johnson*, ed. M.T. Holt and J-P. Chavas, 1–23. Berkley Electronic Press.

Muhammad, A., J.L., Seale . B Meade, and A. Regmi. 2011. *International Evidence on Food Consumption Patterns: An Update Using 2005 International Comparison Program Data.* Washington DC: U.S. Department of Agriculture, Economic Research Service.

Downloaded from http://aepp.oxfordjournals.org/ at University of Wollongong on May 23, 2016

NiMhurchu, C., H. Eyles, M. Genc, P. Scarborough, M. Rayner, A. Mizdrak, K. Nnoaham, and T. Blakely. 2015. Effects of Health-Related Food Taxes and Subsidies on Mortality from Diet-Related Disease in New Zealand: An Econometric-Epidemiologic Modelling Study. *PloS ONE* 10 (7):e0128477.

Pan, S., S. Mohanty, and M. Welch. 2008. India Edible Oil Consumption: A Censored Incomplete Demand Approach. *Journal of Agricultural and Applied Economics* 40 (3): 821–35.

Pashardes, P. 1993. Bias in Estimating the Almost Ideal Demand System with the Stone Index Approximation. *Economic Journal* 103 (419): 908–15.

Pesaran, M.H., and Y. Shin. 2002. Long Run Structural Modelling. *Econometric Reviews* 21: 49–87.

Rickertsen, K. 1998. The Demand for Food and Beverages in Norway. *Agriculutural Economics* 18 (1): 89–100.

Säll, S., and I.M. Gren. 2015. Effects of an Environmental Tax on Meat and Dairy Consumption in Sweden. *Food Policy* 55: 41–53.

Seale, J.L. Regmi., A., and J. Bernstein. 2003. *International Evidence on Food Consumption Patterns*. Washington DC: U.S. Department of Agriculture, Economic Research Service.

Shonkwiler, J.S., and S.T. Yen. 1999. Two-step Estimation of Censored System of Equations. *American Journal of Agricultural Economics* 81 (4): 972–82.

Tiffin, R., and M. Arnoult 2011. The Public Health Impacts of a Fat Tax. *European Journal of Clinical Nutrition* 65 (4): 427–33.

Wirsenius, S., F. Hedenus, and K. Mohlin. 2011. Greenhouse Gas Taxes on Animal Food Products: Rationale, Tax Scheme and Climate Mitigation Effects. *Climatic Change* 108: 159–84.

Zhen, C., E.A. Finkelstein, J.M. Nonnemaker, S.A. Karns, and J.E. Todd. 2014. Predicting the Effects of Sugar-sweetened Beverage Taxes on Food and Beverage Demand in a Large Demand System. *American Journal of Agricultural Economics* 96 (1): 1–25.

Downloaded from http://aepp.oxfordjournals.org/ at University of Wollongong on May 23, 2016