Laura Cornelsen, Mario Mazzocchi,
Richard Smith

Between preferences and references: Evidence from Great Britain on asymmetric price elasticities

Quaderni di Dipartimento

Serie Ricerche 2018, n. 1
ISSN 1973-9346

ALMA MATER STUDIORUM
UNIVERSITÀ DI BOLOGNA

Dipartimento di Scienze Statistiche "Paolo Fortunati"

BETWEEN PREFERENCES AND REFERENCES: EVIDENCE FROM GREAT BRITAIN ON ASYMMETRIC PRICE ELASTICITIES

LAURA CORNELSEN*, MARIO MAZZOCCHI† AND RICHARD SMITH‡

March 26, 2018

Abstract

Canonical demand studies and fiscal policy simulations rest on the assumption that consumers react symmetrically to price increases and decreases. We propose a theoretically consistent demand system which allows for asymmetric response by incorporating reference prices into both own- and cross-prices. Applying the system to a large and detailed home-scan household-level data-set with food prices and purchases from Great Britain, we show evidence on asymmetric consumer response and loss aversion, with a stronger response when prices rise above their reference level. Results are robust to changes in the price definition and model specification, and a simulation shows that ignoring asymmetry may lead to important biases.

JEL: D11, D12, L66, Q11

Keywords: Reference Price, Price Elasticities, Demand System, Food Prices, Loss Aversion

*London School of Hygiene and Tropical Medicine, Faculty of Public Health and Policy, laura.cornelsen@lshtm.ac.uk

†University of Bologna, Department of Statistical Sciences, m.mazzocchi@unibo.it

‡London School of Hygiene and Tropical Medicine, Faculty of Public Health and Policy, richard.smith@lshtm.ac.uk

This research was funded by the UK Medical Research Council (Fellowship in Economics of Health, Grant Ref: MR/L012324/1). The funds were used to purchase data from Kantar Worldpanel UK (KWP). Sally Dudleston from Kantar Worlpanel UK had the right to review the article to ensure the data were not misrepresented. The authors are grateful to Melanie Luhrmann, Rachel Griffith, Timothy Beatty, and Henning Tarp-Jensen for their constructive comments on (very) preliminary versions of this paper, the usual disclaimer applies.

I. Introduction

Canonical micro-economic consumer theory predicts that consumers respond to price increases and decreases with the same intensity. In empirical demand analysis, this means that a single set of price elasticities is estimated, without a distinction between increasing and decreasing prices. The 'symmetry' assumption has been frequently challenged in the marketing literature as unnecessarily restrictive, and empirical counter-evidence has been provided for several goods including soft drinks, eggs, coffee, yoghurt, and peanut butter (Kalyanaram and Winer, 1995).

In his Principle of Economics, Marshall (1920) observed that demand functions may be irreversible, which means that after a price change, its restoration to the previous level does not necessarily bring back demand to the original level. The irreversibility of demand functions has received a good deal of attention in theoretical economics as it provides a justification to observed market price rigidities (Haavelmo, 1944; Heidhues and Kőszegi, 2008). However, empirical analyses have been mostly confined to aggregate demand data for single goods in regulated industries, such as tobacco and spirits (Farrell, 1952), gasoline (Gately, 1992) and telephone calls (Bidwell Jr et al., 1995).

This paper aims to bring sound empirical evidence on this potential asymmetry, while ensuring consistency with the requirements of consumer theory. To this purpose, we include reference price effects in the utility function, and we derive and estimate an Almost Ideal Demand System specification which allows for asymmetric price elasticities.

In July 2017, we ran a Google Scholar search on the terms "Almost Ideal Demand System", "tax" and "subsidy", which returned 3,670 hits. The vast majority of these papers simulates the impact of fiscal policies based on elasticity estimates, and they all assume symmetric elasticities. Departure from this assumption is likely to generate relevant differences in simulations and hence policy conclusions.

Several justifications have been provided to explain asymmetric elasticities, but the most popular rests on framing or threshold effects. More specifically, it is argued that an internal reference price (or price expectation) exists, against which consumers assess the actual price of a good (Winer, 1986; Mazumdar et al., 2005)[1]. The resulting demand curve is kinked in correspondence of the reference price (Drakopoulos, 1992; Kalyanaram and Winer, 1995). Kinked demand curves are consistent with Prospect Theory (Kahneman and Tversky, 1979), as consumers may react stronger to a price increase which generates a loss of utility than to a price decrease leading to an utility gain.

There is, however, one major limitation in the existing body of evidence on asymmetric price elasticities. The studies we have cited limit their focus on individual equations, ignore substitutions completely or estimate these without considering cross-equation constraints such as the properties of adding-up or symmetry.

Understanding cross-price effects is however crucial for interpreting analytical results for policy purposes which often needs to consider both direct and indirect effects of pric-

[1]Other explanations refer to asymmetries in search costs after a price change, habits or addictions, the perception of prices as a proxy for quality and inter-temporal substitutions and stockpiling behaviours

ing. For example, to understand the impact of taxing less healthy foods and beverages, on consumption, it is important to know whether consumers substitute taxed foods and beverages with untaxed alternatives which may or may not be healthier.

Furthermore, as cross-price effects can be either positive or negative with opposite interpretation of consumption change, allowing for asymmetry in cross-price elasticities provides more flexibility in understanding consumer behavior as substitution and complementarity patterns are not forced to apply for both price increases and decreases. If that is the case, then averaging cross-elasticities for price increases and decreases is more likely to yield in estimates close to zero which are less informative for policy interpretation as policy only affects price change in one direction.

One partial exception is the study by Dossche et al. (2010), which extends the Almost Ideal specification to allow for demand to be nonlinear in prices, albeit without an explicit kink or a theoretical justification for the adjusted functional form. Their estimates, based on sales data from a single retailer, are supportive of asymmetric elasticities. However, by focusing on retailer data, it does not allow full estimation of (asymmetric) consumer behavior as consumers can easily switch between retailers, including due to pricing.

The most complete theoretical effort to allow for reference prices within a theoretically consistent demand function is found in Putler (1992). We draw form Putler's work and extend it to allow for asymmetry in both own-price and cross-price elasticities within a demand system framework. We exploit a unique home-scan data-set which follows the individual purchases of food and non-alcoholic beverages of more than 30,000 British households over a two-year time span to provide empirical evidence on the existence, direction and size of asymmetries in consumption responses.

II. Model

A. Irreversible demand functions and reference prices

The first discussion of irreversibility of demand functions is commonly ascribed to Marshall's criticisms of static demand theory in his Principles of Economics[2]:

> It must however be admitted this theory is out of touch with real conditions of life, in so far as it assumes that, if the normal production of a commodity increases and afterwards again diminishes to its old amount, the demand price and supply price will return to their old positions for that amount.

For many years, this irreversibility was seen as a challenge to static demand theory, and the incompatibility of empirical studies on time series data with the assumption of instantaneous adjustment to price changes. This has led to the explicit recognition of dynamic demand schedules and shifting demand curves, especially for food products with frequent price fluctuations (Working, 1932; Mighell and Allen, 1939).

[2]Marshall (1920), Appendix H, paragraph 3

Haavelmo (1944) depicts a dynamic demand schedule, where the demand function $x = f_0(p_0)$ depends on the current level of demand (x_0) and prices (p_0). When prices change from p_0 to p_1, the original demand function predicts the new equilibrium, $x_1 = f_0(p_1)$. However, a new demand function $x = f_1(p_0)$ is needed to predict what happens if prices go back to p_0, and the new consumption level will not necessarily equal x_0, which implies that the demand function is irreversible.

These theoretically irreversible demand functions can be turned into empirically estimable (reversible) demand functions by assuming that the irreversibility scheme is regular. The first empirical treatment of irreversible demand functions dates back to Farrell (1952), but despite the suggestive empirical evidence on asymmetric elasticities and the superior performance of irreversible demand functions, few attempts have been made to provide a theoretical justification based on consumer behavior, resting largely on framing effects and Reference Price Theory, which at the same time are widely studied in marketing science.

The existence of internal reference prices (IRP) is supported by a range of psychological theories (Mazumdar et al., 2005), but the operationalization of the IRP concept in economic models, as discussed later, is based on adaptive rational expectations (Nerlove, 1958). The explicit consideration of adaptive IRPs in the utility or cost function meets our needs, as it allows for both estimable irreversible demand functions and asymmetric elasticities, while ensuring consistency with the theoretical requirements of demand theory. Reversible demand functions and symmetric elasticities become a special case of this generalized framework, that assume perfect expectations (where IRPs equal to actual prices).

B. Consumer choice theory with reference prices

The extension of consumer theory to accommodate (own) reference prices is thoroughly discussed in Putler (1992). Ignoring cross- (reference) price effects is an undesirable limitation, as it prevents the derivation of a theoretically consistent system of demand equations. In other words, it is assumed that consumers only consider the IRP of the good they decide to purchase, but do not perceive marginal gains or losses if the price of a substitute good changes. Putler's theoretical framework can however be easily extended to allow for a complete set of IRPs and full substitution effects.

The utility function is augmented to consider loss (l) and gains (g) deriving from the distance between the actual price (p_i) and the reference price (r_i) of a generic good i. For the rest of the discussion we follow Putler's notation and define an indicator function to discriminate between losses and gains:

$$I_i = \begin{cases} 1 & \text{if } p_i > r_i \\ 0 & \text{if } p_i \leq r_i \end{cases}$$

Hence, consumer losses and gains are defined as $l_i = I_i(p_i - r_i)$ and $l_i = (1 - I_i)(r_i - p_i)$. The augmented utility function is $u = U(u^*, \mathbf{l}, \mathbf{g})$, where $u^* = f(\mathbf{q})$ is the canonical utility function for a consumer basket of n goods, $\mathbf{q} = [q_1, q_2, ...q_n]$ are the purchased quantities, $\mathbf{l} = [l_1, l_2, ..., l_n]$ and $\mathbf{g} = [g_1, g_2, ..., g_n]$ are the vectors containing the perceived losses and gains associated with a change in the price of any of the n goods. The consumer minimizes the total cost x subject to the utility level defined by the augmented utility function:

$$\min_{\mathbf{q}\geq\mathbf{0}} \quad x = \mathbf{p}'\mathbf{q} \quad \text{subject to} \quad U(\mathbf{q}, \mathbf{l}, \mathbf{g}) \geq u \tag{1}$$

The resulting expenditure function E does not only depend on actual prices, but also on reference prices through gains and losses:

$$x = E[\mathbf{p}, \mathbf{I} \circ \mathbf{l}, (\mathbf{1} - \mathbf{I}) \circ \mathbf{g}, u] \tag{2}$$

where $\mathbf{I}$ is a $n \times 1$ vector containing the indicator functions I_i and $\circ$ is the Hadamard (entrywise) product.

From here we proceed in the the usual way. The Hicksian demand functions $\mathbf{q} = h(\mathbf{p}, \mathbf{r}, u)$ are obtained via Shephard's Lemma, and the indirect utility function is obtained by inverting the expenditure function. The Marshallian demand functions $\mathbf{q} = f(\mathbf{p}, \mathbf{r}, x)$ are generated by substituting the indirect utility function into the Hicksian demand functions. These demand functions also have the reference prices among their arguments, as shown in Putler (1992).

The overall effect on demand induced by a change in price p_j is captured by the following generalized Slutsky equation[3]:

$$\frac{\partial f_i(\mathbf{p}, \mathbf{r}, x)}{\partial p_j} = \frac{\mathrm{d}h_i}{\mathrm{d}p_j} + q_j \frac{\partial f_i}{\partial x} + \frac{\partial f_i}{\partial x}\left[(1 - I_j)\frac{\partial E}{\partial g_j} - I_j \frac{\partial E}{\partial l_j}\right] \tag{3}$$

which decomposes the total demand response into a substitution effect, an income effect, and a loss-gain effect. Note that the substitution effect also embodies a loss-gain component through the utility function, and $\mathbf{l}$ and $\mathbf{g}$ are themselves a function of prices, since:

$$\frac{\mathrm{d}h_i(\mathbf{p}, \mathbf{r}, u)}{\mathrm{d}p_j} = \frac{\partial h_i}{\partial p_j} + \sum_{s=1}^{n} \frac{\partial h_i}{\partial l_s}\frac{\mathrm{d}l_s}{\mathrm{d}p_j} + \sum_{s=1}^{n} \frac{\partial h_i}{\partial g_s}\frac{\mathrm{d}g_s}{\mathrm{d}p_j} = \frac{\partial h_i}{\partial p_j} + I_j \frac{\partial h_i}{\partial l_j} - (1 - I_j)\frac{\partial h_i}{\partial g_j} \tag{4}$$

The above generalized Slutsky matrix is still negative semidefinite and symmetric. Negativity follows from the concavity of the expenditure function, which is maintained regardless of its extension to include reference prices. Symmetry of the first addendum in (4) follows from symmetry of the canonical Slutsky Matrix, which implies that $\frac{\partial h_i}{\partial p_j} = \frac{\partial h_j}{\partial p_i}$. Furthermore, under our assumption of adaptive expectations, the reference prices

[3] See Appendix. The equation generalizes Putler's result to the effect of cross-price changes

r_i adjust to price changes with (at least) one period delay, hence they can be treated as pre-determined and exogenous. It follows that $\partial \mathbf{l} = \partial \mathbf{p}$ and $\partial \mathbf{g} = -\partial \mathbf{p}$. Thus, checking symmetry on the remaining terms of the Slutsky equation also reduces to the above condition $\frac{\partial h_i}{\partial p_j} = \frac{\partial h_j}{\partial p_i}$.

C. An Almost Ideal Demand System with reference prices

We extend the flexible functional form of the Almost Ideal Demand System (AIDS) model (Deaton and Muellbauer, 1980) to allow for internal reference price effects and asymmetric elasticities. We choose the AIDS specification because of its popularity and wide application in fiscal simulations, but a similar exercise could be replicated for other theory-based demand system specifications.

The model extension to include reference price effects is relatively straightforward. We start by incorporating reference prices in the AIDS cost function to account for losses and gains as follows:

$$\log C(u, \mathbf{p}, \mathbf{r}) = (1-u)\log a(\mathbf{p}, \mathbf{r}) + u \log b(\mathbf{p}, \mathbf{r}) \tag{5}$$

Where

$$\begin{aligned} \log a(\mathbf{p}, \mathbf{r}) = \alpha_0 &+ \sum_{k=1}^{n} \alpha_k \log p_k + 0.5 \sum_{i=1}^{n} \sum_{j=1}^{n} \gamma_{ij}^* \log p_i \log p_j \\ &+ 0.5 \sum_{i=1}^{n} \sum_{j=1}^{n} \delta_{ij} I_j (\log p_i - \log r_i)(\log p_j - \log r_j) \\ &- 0.5 \sum_{i=1}^{n} \sum_{j=1}^{n} \omega_{ij} (1 - I_j)(\log r_i - \log p_i)(\log r_j - \log p_j) \end{aligned} \tag{6}$$

and

$$\log b(\mathbf{p}, \mathbf{r}) = \log a(\mathbf{p}, \mathbf{r}) + \beta_0 \prod_{k=1}^{n} p_k^{\beta_k}$$

So that the cost function becomes

$$\log C(u, \mathbf{p}, \mathbf{r}) = \log a(\mathbf{p}, \mathbf{r}) + u\beta_0 \prod_{k=1}^{n} p_k^{\beta_k}$$

The derivation of the Marshallian demand function follows the usual AIDS procedure, i.e. (a) the first derivative of the cost function with respect to prices generates the Hicksian demand functions; (b) the indirect utility function is obtained through inversion of the cost function with respect to u; (c) substitution of the indirect utility function into the

Hicksian demand function generates a Marshallian demand function of the form:

$$\begin{aligned} w_i = \alpha_i + \sum_{j=1}^{n} \gamma_{ij} \log p_j + \sum_{j=1}^{n} \delta_{ij} I_j (\log p_j - \log r_j) \\ - \sum_{j=1}^{n} \omega_{ij} (1 - I_j)(\log p_j - \log r_j) + \beta_i \log \left(\frac{x}{P} \right) \end{aligned} \tag{7}$$

where $w_i = \frac{p_i q_i}{x}$ is the expenditure share for the i-th good and losses and gains are incorporated through the indicator function I_j. The model implies that for example if losses occur, the expenditure share for each good is a function of its own price, prices for other goods in the model, loss in the own price and losses or gains in other prices, and total expenditure indexed through P, which is a non-linear price index specified as follows:

$$\begin{aligned} \log P = \alpha_0 + \sum_{k=1}^{n} \alpha_k \log p_k + 0.5 \sum_{i=1}^{n} \sum_{j=1}^{n} \gamma_{ij}^{*} \log p_i \log p_j \\ + 0.5 \sum_{i=1}^{n} \sum_{j=1}^{n} \delta_{ij} I_j (\log p_i - \log r_i)(\log p_j - \log r_j) \\ - 0.5 \sum_{i=1}^{n} \sum_{j=1}^{n} \omega_{ij} (1 - I_j)(\log r_i - \log p_i)(\log r_j - \log p_j) \end{aligned} \tag{8}$$

In addition to the usual AIDS adding-up conditions, the model with reference prices requires the following additional constraints to be met:

$$\sum_{i=1}^{n} \delta_{ij} = \sum_{i=1}^{n} \omega_{ij} = 0$$

Furthermore, symmetry not only must hold for the γ_{ij} parameters, but also for the additional ω_{ij} and δ_{ij} parameters.
Homogeneity is a more complex matter. If all prices and the total budget are multiplied by a constant κ, but reference prices remain unchanged, the resulting demand equation is:

$$\begin{aligned} w_i = \alpha_i + \log \kappa \sum_{j=1}^{n} \gamma_{ij} + \sum_{j=1}^{n} \gamma_{ij} \log p_j + \log \kappa \sum_{j=1}^{n} \delta_{ij} I_j + \log \kappa \sum_{j=1}^{n} \omega_{ij} (1 - I_j) \\ + \sum_{j=1}^{n} \delta_{ij} I_j (\log p_j - \log r_j) + \sum_{j=1}^{n} \omega_{ij} (1 - I_j)(\log p_j - \log r_j) + \beta_i \left(\frac{\kappa x}{P(\kappa)} \right) \end{aligned}$$

where $P(\kappa)$ is the non-linear price index in (8) where all prices are multiplied by κ. It can be shown that for homogeneity to hold, it is necessary that in each equation of the system $\sum_{j=1}^{n} \delta_{ij} I_j = 0$ and $\sum_{j=1}^{n} \omega_{ij}(1 - I_j) = 0$. This is a more restrictive condition than $\sum_{j=1}^{n} \delta_{ij} = 0$ and $\sum_{j=1}^{n} \omega_{ij} = 0$, which are implied by the imposition of adding-up and symmetry on three additional coefficients. Thus, as already discussed in Putler (1992), homogeneity does not necessarily hold in a consumer model with reference price effects.

D. Asymmetric elasticities

The introduction of reference prices implies the estimation of two sets of Marshallian price elasticities, thus allowing for asymmetric response, depending on the values of the indicator function I_j, i.e. whether the changing price is above or below the reference price.

$$
\begin{aligned}
e_{ij} &= \frac{\partial \log q_i}{\partial \log p_j} = \frac{\partial w_i}{\partial \log p_j} \frac{1}{w_i} - \frac{\partial \log p_i}{\partial \log p_j} \\
&= \frac{\gamma_{ij}}{w_i} + \frac{\delta_{ij} I_j}{w_i} - \frac{\omega_j (1 - I_j)}{w_i} - \frac{\beta_i}{w_i} \eta_{ij} - \Delta_{ij}
\end{aligned}
\qquad (9)
$$

where

$$
\begin{aligned}
\eta_{ij} = \frac{\partial \log P}{\partial \log p_j} &= \alpha_j + \sum_{k=1}^{n} \gamma_{kj} \log p_k + \sum_{k=1}^{n} \delta_{kj} I_j (\log p_j - \log r_j) \\
&- \sum_{k=1}^{n} \omega_{kj} \left(1 - I_j\right) \left(\log p_j - \log r_j\right)
\end{aligned}
$$

and $\Delta_{ij} = 1$ when $i = j$ and 0 otherwise.

E. Empirical definition of reference prices

Internal reference prices are operationally treated as rational expectations, where the expected price is a function of one or more prices experienced in the past (Muth, 1961). The most common choice is to set the IRP equal to a single previous purchase price, whereas more elaborate definitions refer to a combination of prices consumers may hold in their memory (Kalyanaram and Winer, 1995).

The most common definition implies that consumers have in mind one price from the past, which they compare with the shelf price. Hence, the reference prices for good i at time t is:

$$
r_{it} = p_{is} \quad \text{with} \quad s \leq t - 1 \qquad (10)
$$

The obvious choice for the reference period s is the previous period. When a single good is considered, the usual choice is to set the reference price equal to the last purchase price of that good. However, this choice might be unnecessarily restrictive. Consumer may decide not to purchase a good while knowing its price, as they decide to allocate their budget to substitute goods. Given that in our theoretical setting the consumer is assumed to assess the (reference) prices of multiple goods, a more realistic choice is to use as reference prices those corresponding to the latest shopping trip where at least one purchase was made, regardless of which food(s) were purchased:

$$r_{it} = p_{is} \quad \text{with} \quad \underset{z}{\text{argmax}}\ s = \{z \in (1, t-1) \,|\, \exists k \in (1, n) : q_{kz} > 0\} \tag{11}$$

Reference prices may also be assumed to include a combination rather than just one previous price, as in adaptive theories. In this case an extrapolative expectation model can be specified (Nerlove, 1958; Kalwani et al., 1990; Putler, 1992), where the reference price is a geometrically weighted moving average of a set of past prices of the same good, and the weights are normalized to sum to one:

$$r_{it} = \left(\sum_{h=1}^{L} \rho_i^h \right)^{-1} \sum_{s=1}^{L} \rho_i^s p_{i,t-s} \tag{12}$$

where L is the number of lags being considered, and $0 < \rho_i \leq 1$ is a good-specific parameter to be estimated through a distributed lag model.

Defining IRPs as rational expectations provides the condition which makes the irreversibility scheme regular. When prices change, not only do they affect current demand, but they also induce modifications in reference prices for the next period, hence generating a shift in the demand schedule.

III. Data

A. Raw Data

The lack of empirical demand studies on reference price effects and asymmetric elasticities finds a justification in the historical scarcity of adequate data. A high time frequency and geographical detail are required to process meaningful price and purchase information. Data limitations have been recently overcome by the growing availability of large-scale commercial home-scan panels.

We use secondary Great Britain (GB) household expenditure data from January 2012 to December 2013, purchased from Kantar Worldpanel UK. Our data include information on all household food and non-alcoholic drinks purchases for consumption at home. Purchases are made in a variety of outlets, such as major retailers, supermarkets, butchers, greengrocers, and corner shops. Kantar Worldpanel UK has been collecting this data since 2006. The company recruits participants via postal mail and e-mail. Data are collected from each participant household via supplied hand-held scanners which households use to scan barcodes of all purchased products. Barcodes to use for products where these are missing (e.g. loose fruit and vegetables from a market) are supplied to households. Additionally, households send digital images of till receipts. Participants are offered vouchers for retailers and for leisure activities of average value of £100 per household per year.

The data is collected from a sample of GB households ($n = 32,726$ in 2012 and $n = 32,620$ in 2013) stratified according to household size, number of children, social class, geographical region and age group. The joint data-set includes $n = 36,324$ distinct households, of which 80% ($n = 29,022$) appear in both the 2012 and 2013 sample.

Our raw data-set consists of individual transactions, including information on the day of the purchase, outlet, amount spent, and volume purchased. In addition, socio-demographic data, collected annually, describes household size and composition, age, ethnicity and highest qualification of the main shopper. It also includes information on the geographical location (postcode district), income group, social class and tenure of the household.

There are about 72 million transactions in our data-set, which implies a major trade-off between the precision of highly disaggregated data and their meaningful use in demand analysis. The basic observation is the individual transaction with a bar-code detail, which means that products are disaggregated to the brand and package level, e.g. a 33cl Cola can be considered as a distinct good from a 1lt bottle. Having information on the purchase date, outlet and household postcode means that the information on the exact day of price change within a given area is potentially available. However, using this level of detail is not viable at the barcode level, as it requires that every day at least one household in the same postcode district purchases that specific product in a specific outlet. The chosen level of disaggregation also impacts on some well-known demand system estimation issues, such as the proportion of zero-expenditure observations and the endogeneity of total expenditure. When aggregation choices are made, their impact on the estimates is unknown and remains to be explained.

The statistical unit for our model is the household, and as our focus is on budget allocation and substitutions, a daily frequency would lead to the inclusion of a large number of observations consisting of a small number of often single purchases. This would imply a very strong endogeneity of the total expenditure term on the right hand side of the demand system. As the vast majority of households make at least one food shopping trip per week, we use weeks as the basic time unit.

B. Food purchases, aggregation and composite prices

Aggregation of individual products into food categories is common in the empirical demand analysis literature for several reasons. First, standard household budget surveys have a limited level of product detail, generally corresponding to food groupings based on the UN COICOP classification, e.g. soft drinks, whole milk, or apples, with no brand or packaging distinction. Second, aggregation across individual foods minimizes the frequency of non-purchases. Third, food groups are more interesting from a policy perspective, as simulations to inform fiscal policies, such as taxes or subsidies to promote healthier eating, are concerned with substitutions at the food group level rather than brand competition.

However, aggregation comes at a cost, as the actual prices paid by the consumer are summarised into composite prices. These composite prices, or unit values, incorporate a quality choice dimension, whose relevance depends on the heterogeneity of the actual prices of the goods which form the aggregate (Deaton, 1988).

Our data, as most household budget surveys, reports the quantity purchased and the amount spent for a product, and the unit value can be obtained by dividing expenditure by quantity. Only at the maximum level of product detail, this unit value corresponds to the shelf price, but even in this case it would embody a quality component because of the choice of the retail outlet. Consumers do not choose between outlets depending on the prices of individual products, but they rather decide where to shop based on an expectation of the cost and quality of their food basket. Thus, two households living in the same building, or even two consumers living in the same household, may pay a different price for the same product in the same day. These issues need to be addressed before demand estimation.

Food Purchases. We estimate two conditional demand systems incorporating reference prices and allowing for different levels of product detail. First, we estimate a three-good AIDS model conditional on total cola beverage expenditure, considering the following three goods: (a) standard cola of a selected brand in bottles of 1-litre or more (X-Cola 1L+); (b) all other colas of the same brand, regardless of packaging and size (X-Cola other); (c) all colas of any other brands, regardless of packaging and size (Other brands). Within this system, the first good represents the maximum level of disaggregation in the data-set, while showing an acceptable frequency of purchase across households and over time.

Second, we estimate a four-good AIDS model conditional on total food and beverage expenditure (excluding alcoholic drinks) using larger food groupings which may be relevant to nutrition-targeted fiscal policies. The goods being modelled are: (a) fresh fruits, vegetables and salad products (including chilled prepared products); (b) savoury snack products (potato, vegetable or corn crisps, prawn crackers, crackers, poppadoms, pork scratchings, snacking nuts and pop-corn); (c) non-alcoholic drinks (including soft drinks, cordials, fruit juices and water but excluding flavoured milk and yoghurt drinks); (d) all other food products.

We reshape the transaction-level raw data into a pooled data-set where the basic observation is a household/week. For each of the aforementioned food groups we sum the purchased volume and amount spent over each household and week. Considering the complete data-set of 36,324 households, on average each household reports food purchases on 83 weeks out of the 104 available, with 7% of the households purchasing food in each of the 104 weeks.

Prices. Unit values for each food group are calculated as the ratio of the amount spent over the quantity purchased. To deal with the quality choice component in unit values, we follow the standard assumption that households living in the same area face the same prices in the same week (Deaton, 1988). Since we follow a system-wise approach, this approach also provides us information on the price of substitute goods which have not been purchased.

The households in our data-set are classified into 110 postcode areas[4], and we exploit this geographical disaggregation to obtain an estimate of local prices for all food groups by averaging the unit values paid within each postcode and week:

$$p_{ict} = \frac{\sum_{h \in A_c} x_{iht}}{\sum_{h \in A_c} q_{iht}} \tag{13}$$

where x_{iht} is the amount spent in period t by a household h to purchase all products included in the food group i, q_{iht} is the corresponding aggregated quantity, and A_c with $c = 1, ..., 110$ is the set of households living in the $c-$th postcode area. With this basic adjustment, we compute prices for all food groups and have variation across postcodes c and time periods t.

An alternative approach, which we apply to check for robustness, is based on the industry wide agreement on national pricing policy between food retailers and the UK Competition Commission (Nakamura et al., 2015). According to the agreement, supermarkets apply the same prices in the same types of its shops in all of the UK branches (e.g. products have the same price in all Tesco Metro branches which may differ from the prices in Tesco Express branches). Thus, we aggregate prices based on households shopping in the same type and brand of outlet, so that A_c in (13) reflects the set of household shopping in the c-th outlet.

C. Sample description

The final sample for our analysis includes all households with positive total expenditure on the selected goods for at least two weeks over the two-year period. Table 1 presents descriptive statistics. After aggregation and deletion of observations with missing values in demographic variables, the final data-set contains 2.15 millions of observations on 30,740 households, and on average each household reports food purchases in 70 weeks. The demographic statistics are in line with the official statistics for Great Britain[5].

Table 2 reports average quantities, expenditure and prices for the samples used in estimation. The Cola model has a smaller number of households and observations, as only those observations (household-weeks) where at least one cola is purchased are considered. As one might expect, the proportion of non-purchases strongly depends on the level of product aggregation. Although about 80% of the households have bought cola at least once in the two-year period, only 11.4% of the observations include a purchase of the X-Cola 1L+, whereas other brand colas account for 56.8% of the weekly purchases. On

[4]Postcode area is defined based on the letters in the first half of the postcode the household resides in. Great Britain has 120 postcode areas, which depend on the area being served. For example London has eight postcode areas, while other cities (e.g. Liverpool, Birmingham) only one. We aggregated some postcode areas in London, Scotland and Wales to ensure that at least 5 household per week were present

[5]Office for National Statistics web site, www.ons.gov.uk

Table 1. Sample Descriptive Statistics.

	Mean	St. Dev.
Household size	2.64	1.32
Age of main shopper	50.87	14.84
Number of children	0.59	0.96
Number of children if have children	1.76	0.82

	Percent of Households
Households with children	33.4
Income	
£0 - £9,999 pa	10.4
£10,000 - £19,999 pa	25.9
£20,000 - £29,999 pa	21.9
£30,000 - £39,999 pa	15.9
£40,000 - £49,999 pa	11.2
£50,000 - £59,999 pa	6.6
£60,000 - £69,999 pa	3.5
£70,000 +	4.6
ONS Social Grade	
Class AB	20.8
Class C1	37.7
Class C2	18.1
Class D	13.4
Class E	10.0
Education of RP (highest qualification)	
Degree or higher	26.6
Higher education	15.1
A Level	12.9
GCSE	22.0
Other	9.2
None	9.5
Tenure Type	
Owned outright	29.6
Mortgaged	41.1
Rented	28.0
Other	1.4
Number of households	30,740
Number of observations	2,157,395

average, the total weekly quantity bought by cola purchasers across the three categories is similar, ranging from 4.4 lt to 4.8 lt.

The table also shows the average price, which is the average of the geographical prices across the postcode areas. The difference between the average price and the average unit value paid by purchasing households (last column in Table 2) is a matter of weighting. By averaging across households within the same week and postcode areas, geographical price mitigate the quality and aggregation issue.

Unit values reflect the quality component, and averaging across the whole sample assigns a larger weight to those postcode areas with a higher number of purchasing households. Quality heterogeneity in the purchased products, such as a branded product and variation in packaging and price across different stores makes the difference between average prices and unit values larger, and this difference becomes larger as categories aggregate a larger number of products and brands. For example, the average geographical price per litre of X-Cola 1L+ is identical to the average unit values paid by purchasing households, since there is no quality heterogeneity in the purchased products and very little variation in packaging and prices across different stores.

The distance between the two averages in the X-Cola Other group reflects heterogeneity in household choices, mainly related to packaging, as products are available in different sizes, and smaller sizes (e.g. cans) have a higher unit value. In the Other Cola group the difference becomes even larger as the category aggregates over different brands and sizes. Geographical prices are expected to cancel out, or at least mitigate, this aggregation issue, as households within the same postcode are assumed to face the same set of prices. Local demand shocks are also unlikely to affect the average prices due to the voluntary National Pricing Policy within same types of stores (e.g. prices in Tesco Extra in London would be the same as Tesco Extra in Liverpool).

These considerations are amplified when food groups are considered. The more heterogeneous the category (fruit & vegetables, other foods), the lower the percentage of non-purchases, and greater the difference between geographical average prices and unit values.

The dynamics in prices faced by households relative to the alternative definitions of reference prices are presented in Table 3. We consider two alternative definitions of reference prices: (a) lagged geographical prices; and (b) adaptive expectations.

The proportion of losses and gains, where the former represent those weeks where the price is above the household reference price and vice versa, is relatively balanced across all products, both for the cola and food groupings. Values in parentheses are the average percent distance from reference price when a loss (gain) is experienced. The extent of price variation experienced by cola shoppers is much larger than the one observed for the food model.

Again, this may be explained by the level of product aggregation and category heterogeneity. Consumers facing a higher price for fruit, for example, have a much wider choice of within category substitution relative to the cola categories.

Our second definition refers to adaptive expectation IRPs, based on the extrapolative

Table 2. Purchase Data.

	All observations			Purchases	Purchases only		
	Exp	Vol	Price	Percent	Exp	Vol	Unit value
				Cola model			
X-Cola (1lt+)	0.33	0.50	0.69	11.4	2.89	4.36	0.69
	(1.14)	(1.76)	(0.10)		(2.02)	(3.22)	(0.19)
X-Cola (other)	1.63	1.85	0.99	40.4	4.05	4.58	1.09
	(2.91)	(3.44)	(0.14)		(3.35)	(4.09)	(0.58)
Other brands	1.39	2.73	0.48	56.8	2.44	4.82	0.57
	(2.16)	(4.04)	(0.07)		(2.36)	(4.32)	(0.40)
Total Cola	3.35	5.09		100.0			
	(3.11)	(4.48)					
Households	24,433						
Observations	420,770						
				Food model			
Fruit & Veg	6.59	3.89	1.73	85.3	7.72	4.55	2.00
	(6.60)	(3.72)	(0.17)		(6.51)	(3.63)	(1.44)
Snacks	1.35	0.20	6.91	44.8	3.01	0.45	7.48
	(2.19)	(0.33)	(0.39)		(2.40)	(0.37)	(3.32)
Soft drinks	2.35	3.50	0.69	56.8	4.13	6.17	0.83
	(3.66)	(5.51)	(0.05)		(4.02)	(6.08)	(0.68)
Other foods	37.09	20.87	1.83	99.5	37.16	20.97	2.09
	(26.92)	(16.04)	(0.12)		(26.83)	(16.02)	(2.58)
Total Food	47.28	28.46		100.0			
	(33.08)	(20.66)					
Households	30,740						
Observations	2,157,395						

Notes: Standard deviations in parentheses. Food quantities are expressed in kilograms and drink quantities in litres per week. Expenditures are in Sterling Pounds (£) per week. Prices and unit values are in £/Kg. or £/Litre. Prices are the average of unit values by postcode area. Unit values are the ratio between expenditure and quantity by household. Purchases refer to the household weeks with non-zero expenditure.

Table 3. Proportion of Losses and Gains, and Average Distance from Reference Price.

	Lagged Price		Reference Price Adaptive Expectation		Lagged Price (5% trim)	
	Loss	Gain	Loss	Gain	Loss	Gain
X-Cola (1lt+)	45.9	47.8	48.6	51.4	34.3	36.3
	(13.7)	(−14.0)	(12.8)	(−12.9)	(17.5)	(−17.6)
X-Cola (other)	47.4	47.3	49.1	50.9	35.1	35.2
	(12.8)	(−12.9)	(12.1)	(−11.9)	(16.4)	(−16.6)
Other brands	47.1	47.6	48.8	51.2	34.3	34.7
	(12.7)	(−12.6)	(11.9)	(−11.5)	(16.5)	(−16.4)
Fruit & Veg	50.4	48.3	50.2	49.8	16.2	14.9
	(4.2)	(−4.0)	(3.8)	(−3.9)	(8.1)	(−8.0)
Snacks	49	49.7	49.5	50.5	17.2	16.8
	(4.4)	(−4.3)	(3.8)	(−3.8)	(8.4)	(−8.2)
Soft drinks	49.6	49.1	49.3	50.7	21.6	21.7
	(5.5)	(−5.4)	(4.6)	(−4.6)	(9.4)	(−9.3)
Other foods	50.7	48.0	50.7	49.3	13.3	12.2
	(3.6)	(−3.7)	(3.2)	(−3.4)	(7.6)	(−7.8)

Note: Figures show the proportion of losses (actual price above the reference price) and gains (actual price below the reference price. The figure in brackets is the average distance between the actual price and the reference price conditional on losses (gains). The 5% trim means that price gaps are classified as losses or gains only when the distance between actual prices and reference prices exceeds 5%.

expectation model (12). Using adaptive expectations makes very little difference, except that the average variations are slightly smaller[6]. When this formulation is adopted, all observations are classified as losses or gains, and there is no such thing as the price meeting expectation. The share of losses and gains is around 50%, as for the geographical lagged price specification.

To avoid erroneously interpreting the noise introduced by aggregation across individual products as a price change, we check for the robustness of our elasticity estimates to a stricter definition of losses and gains, which only occur when the distance between the actual price and the reference price exceeds 5% (the last two columns in Table 3). Variations below this threshold are still considered in elasticity estimation, but they only affect average elasticity, and not the asymmetry led by the losses and gains. Trimming observations within this range strongly reduces their occurrence and increases the average magnitude of losses and gains, especially for the food categories where price variation is smaller. The balance between losses and gains remains similar to the other reference price definitions.

[6] We set the number of geometric lag to five, but we tested for different lag numbers, which made almost no difference in reference price estimates

IV. Estimation strategy

The augmented AIDS model which allows for reference prices described in equation (7) can be estimated as any standard AIDS model. Since its introduction, the AIDS model has sparkled a vast literature addressing empirical estimation challenges associated with the nature of the data, and proposing a variety of solutions (Blundell, 1988). These deal with the presence of zero observations (non-purchases), the endogeneity of the total expenditure variable on the right-hand side of the equations, the use of unit values instead of retail prices, and the need to account for heterogeneity in household characteristics and preferences. In robustness analyses, we check to what extent asymmetric estimates from our model depend on the different estimation choices choices in dealing with these issues.

As shown in Table 2, the disaggregation level of our data implies a varying proportion of household-weeks with no purchases in a specific group. Failing to consider the right-hand censoring generates a selection bias which affects the estimation of the behavioral parameters and demand elasticities. The problem of selection bias is generally addressed using two-step estimation procedures, where the first step involves the estimation of a discrete choice selection model to obtain the probability of non-zero purchases given a set of household characteristics. In the second step this probability enters the AIDS model to improve the consistency of the parameter estimates.

Different two-step methods have been proposed in the literature, where an important aspect is whether estimates of the second-step AIDS model are based on the full sample, or only on non-zero observations. The latter approach follows the standard Heckman selection model, and is undesirable when working with systemwise estimation on data-sets which - like ours - have a large proportion of non-purchases. We adopt the alternative formulation described in Shonkwiler and Yen (1999) and Tauchmann (2005), makes use of the full estimation sample and is common in the empirical literature. The first stage probit equation is defined as:

$$z_{iht} = \tau_{i0} + \sum_{b=1}^{k} \tau_{ib} d_{hbt} + \sum_{c=1}^{12} \zeta_{ic} s_{ct} + \rho_i q_{ih,t-1} + u_{iht} \tag{14}$$

where

$$z_{iht} = \begin{cases} 1 & \text{if } q_{iht} > 0 \\ 0 & \text{if } q_{iht} \leq 0 \end{cases}$$

is the binary variable discriminating between purchases and non-purchases of good i for household h at time t, and is expressed as a function of a set of k household characteristics d_{hbt}, $b = 1, ..., k$, of thirteen 4-weekly effects s_{ct} to control for seasonality in purchase patterns, and of lagged purchases $q_{ih,t-1}$ to allow for stockpiling. The household characteristics we consider in our model are those listed in Table 1, that is household size, age of the main shopper, household income, and dummies to capture the education level of the main shopper, the household social grade, the tenure type and the presence of children aged under 15 in the household. Based on the maximum likelihood estimates of equation (14), we compute, for each household, week and good, the probabilities from standard normal density function $\phi_{\text{iht}}\left(z_{iht}^{*}\right)$ and the cumulative distribution function $\Phi_{iht}\left(z_{iht}^{*}\right)$, where z_{iht}^{*} are the predictions from the probit model. These estimates enter the second estimation step as follows:

$$w_{iht} = \phi_{\text{iht}}\left(z_{iht}^{*}\right) f_{iht} + \theta_i \Phi_{iht}\left(z_{iht}^{*}\right) \tag{15}$$

where f_{iht} is the right-hand side expression in the AIDS model (7) for good i, household h and time t:

$$\begin{aligned} f_{iht} = \alpha_i + \sum_{j=1}^{n} \gamma_{ij} \log p_{hjt} + \sum_{j=1}^{n} \delta_{ij} I_{hjt} (\log p_{hjt} - \log r_{hjt}) + \\ - \sum_{j=1}^{n} \omega_{ij} (1 - I_{hjt})(\log p_{hjt} - \log r_{hjt}) + \beta_i \log\left(\frac{x_{ht}}{P_{ht}}\right) \end{aligned}$$

where P_{ht} is the non-linear price index defined in (8), p_{hjt} is the price for good j faced by household h at time t, and r_{hjt} is the corresponding reference price. As before, the losses and gains enter the model through the indicator function.

Our empirical specifications rest on the assumption of weak separability, and our models are conditional on total cola expenditure and total food and drink expenditure, respectively. To deal with the endogeneiy of the total expenditure, in the baseline specification we instrument total expenditure (on either cola or food and beverage), using household income, a set of 4-weeks dummies to account for seasonality, and other household characteristics.

A third source of bias is related to the aforementioned unit value issue, associated with quality choice heterogeneity and aggregation, which led us to use average unit values by postcode area and week as a proxy for the prices. While averaging mitigates the problem, a further correction may be necessary if there exist large disparities in household characteristics across post-codes, so that the difference in average unit values between postcode areas might not only reflect actual price differences. We use a two-step approach which draws from Deaton (1988). First, for each good, we demean logs of unit values, logs of purchased values, all household demographics, and 13 four-weeks seasonal dummies. Second, we run a regression with the demeaned unit values on the left-hand side, and with demeaned quantities, demographics and seasonal dummies on the right hand side:

$$(\ln v_{iht} - \ln \overline{v_{ict}}) = \sum_{b=1}^{k} \lambda_{ib} (d_{ht} - \overline{d_{ct}}) + \phi_i (\ln q_{iht} - \ln \overline{q_{ict}}) + \upsilon_{iht} \tag{16}$$

where v_{iht} is the unit value paid by household h for good i at time t, $\overline{v_{ict}}$ is the average of unit values for good i in postcode area c, d_{ht} is a set of household demographics (and seasonal dummies), d_{ct} is the corresponding postcode average, q_{iht} is the quantity of the good purchased by the household, and $\overline{q_{ict}}$ the corresponding postcode average.

The adjusted prices (including the reference ones) for each good , postcode and week are then obtained from the average unit values by applying the coefficient vectors λ and ϕ as follows:

$$\ln p_{ict} = \ln \overline{v_{ict}} - \sum_{b=1}^{k} \lambda_{ib} \overline{d_{ct}} - \phi_i \ln \overline{q_{ict}} \tag{17}$$

Finally, we augment the model to allow for household heterogeneity. We adopt two alternative routes for this purpose. First, we augment the AIDS model by adding demographic variables as intercept shifters. Second, we re-estimate the model with household fixed effects. Econometric estimation under this specification is not trivial when the number of households is so large, thus we estimate the linearized version of the AIDS model, substituting the non-linear price index with the Stone index.

While this variety of specifications and estimation issues might seem redundant, our goal is to check whether the model specification and asymmetric elasticities are robust to these choices.

V. Results

Own-price Marshallian elasticities estimated by the AIDS extension to include reference prices, are shown in Table 4. Our baseline specification is the two-step model in (15), and total expenditure is instrumented to account for endogeneity. We show the results for the canonical symmetric AIDS model in the first column of the table. Asymmetric own-price elasticities are reported under the two different price definitions described in section II., using the price from the last shopping trip as the reference price (11), and the reference price from the extrapolative expectation model as in (12). For both specifications we report the elasticity associated with losses, i.e. when the current price exceeds the IRP, and with gains, i.e. when the current price is lower than the IRP. To check for the sensitivity of estimates to price measurement noises, the last two columns refer to estimates when the price at the last shopping is the IRP, but losses and gains only occur if the gap between the price and the IRP is above 5%.

Price elasticities can be thought of a combination of two different sources of price variability: (a) cross-sectional variation within the same time period, in our case price variation across post-codes; (b) time variation in prices faced by the same household, which in our case is reduced to the postcode price variation over time. Canonical models do not explicitly decompose these two sources of variability. Our augmented model, together with a definition of IRPs based on rational expectations and lags, separates the effect of time variation and further splits demand response into two separate elasticities, depending on whether households are in a loss or gain situation. Symmetric elasticities in Table 4 can be seen as the final combination of these sources of variability.

Considering the cola model, the own-price elasticity values are plausible and show relatively smaller own-price elasticity for the X-Cola 1L+ relative to other colas from the same brand and to the aggregate group of colas from all other brands. The distinction between losses and gains confirms an established result from the empirical literature in line with consumer loss aversion, as own-price elasticities are larger under losses relative to gains (Kalyanaram and Winer, 1995; Meyer and Johnson, 1995). Our theoretically-consistent system wise specification, however, points at an interesting result. The asymmetry in demand elasticity is strongest for other cola brands. This would have implications to a firm's pricing strategy; particularly as in a consumer gain situation the demand for other cola brand beverages is much less elastic in comparison to X-cola. With symmetric elasticity estimates this imbalance between brands would be hidden.

The size of our data-set and the precision of our estimates provides strong support to the asymmetric elasticity hypothesis, and changing the price definition or trimming only bring minor differences to the estimates and no detectable difference in terms of goodness-of-fit.

These results are confirmed in the food model. As expected, the asymmetry is less evident, and becomes negligible as foods are aggregated into larger groups, to the point that the elasticites in the residual group including all other foods are almost identical to the symmetric ones. After trimming, the asymmetry is still clear for snacks and soft drinks, albeit smaller for fruit and vegetables.

Relative to previous evidence, our model has the advantage of providing theoretically consistent cross-price elasticities allowing for differential response depending on whether prices increase or decrease. These are presented in Table 5. As it is often the case with aggregated goods, substitution elasticities are relatively small, and the asymmetry is also less conspicuous, albeit still large relative to standard errors. Again, changing the definition of the reference price does not bring major differences in the estimates, or the direction of their asymmetry.

Some results are, however, intriguing. For example, consider the competition between X-Cola (other) products and other brands. When X-Cola raises their price above the reference (hence a loss situation for the X-Cola other group in Table 5), we find a strong substitution towards other brand colas with a cross-price elasticity of 0.658. However, in case of a price cut which brings price below the reference (a gain situation), the substitution away from other brand colas is much smaller in comparison, around 0.095 – something the symmetric elasticity would have overestimated by five-fold (0.498). Consider now the opposite situation. Under symmetry, other brand colas have a small (0.049) positive cross-price elasticity towards X-Cola (other), indicating these are substitute products. When accounting for reference price effects, the substitution effect holds only if the price of other brands goes above the reference, as demand for X-Cola increases (a cross-price elasticity of 0.211). However, if other brands cut prices below the reference, X-Cola (other) products become complements, as cross-price elasticities are negative and large (-0.363), hence indicating an increase in X-Cola (other) demand too. Interestingly, the demand for other brand colas does not respond to increases in prices of X-cola 1lt+, but it is a complement (and demand for other brand colas increases) when the price of X-Cola 1lt+ is cut.

Table 4. Own-price elasticities.

	Symmetric	Reference Price					
		Lagged Price		Adaptive Expectation		Lagged Price (5% trim)	
		Loss	Gain	Loss	Gain	Loss	Gain
			Cola model				
X-Cola (1lt+)	−0.985	−1.073	−0.892	−1.089	−0.877	−1.068	−0.897
	(0.009)	(0.013)	(0.012)	(0.012)	(0.013)	(0.012)	(0.012)
X-Cola (other)	−1.431	−1.627	−1.004	−1.650	−0.915	−1.601	−1.026
	(0.041)	(0.038)	(0.038)	(0.037)	(0.045)	(0.036)	(0.037)
Other brands	−1.115	−1.324	−0.642	−1.347	−0.547	−1.297	−0.666
	(0.046)	(0.045)	(0.046)	(0.045)	(0.052)	(0.044)	(0.045)
Obs.	400,437	399,980		400,437		399,980	
RMSE	0.359	0.359		0.359		0.359	
			Food model				
Fruit & Veg	−1.363	−1.303	−1.194	−1.285	−1.087	−1.264	−1.193
	(0.014)	(0.019)	(0.024)	(0.017)	(0.019)	(0.010)	(0.011)
Snacks	−0.977	−1.037	−0.899	−1.043	−0.905	−1.005	−0.872
	(0.028)	(0.033)	(0.029)	(0.032)	(0.029)	(0.022)	(0.023)
Soft drinks	−1.056	−1.096	−0.933	−1.132	−0.888	−1.038	−0.902
	(0.023)	(0.027)	(0.029)	(0.028)	(0.028)	(0.019)	(0.020)
Other foods	−1.019	−1.014	−1.004	−1.013	−0.995	−1.010	−1.003
	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)
Obs.	2,055,686	2,055,685		2,055,674		2,055,686	
RMSE	0.126	0.126		0.127		0.126	

Note: Standard errors in parentheses. All standard errors are clustered by postcode area (110 postcode areas).

Good evidence of asymmetric cross-price elasticities also emerges for the food model. Given the nutrition and health implications of these food groupings, looking at the cases where switching from losses to gain turns two goods from substitutes to complements or vice versa is especially important. For example, we find that under the symmetric elasticity scenario and if prices increase above reference, soft drinks and snacks are largely unrelated as price change in one does not affect the demand for the other. However if prices of either snacks or soft drinks are cut, the two food groups become complements, leading to an increase, albeit a small one, in the consumption of the other products (cross-price elasticity of 0.12 and 0.15, respectively).

A. Robustness checks

We now turn our attention to the role played by choosing a specific price definition or model specification in detecting asymmetry. Tables 6 and 7 present the elasticity gaps, intended as the difference between loss and gain elasticities, under different reference price definitions[7]. The first three columns correspond to the three reference prices considered in the previous two tables, and the elasticity gaps are very similar. The fourth column (Model 3) incorporates the adjustment for unit value bias as in (16) and (17).

Relative to the baseline model, the differences are very small, and mostly in the direction of stronger asymmetries. Model 4 shows the elasticity gaps when prices are clustered by retailer rather than by postcode area, under the assumption that the same retailer applies the same price in the same type of its outlets. Since households might shop in more than one outlet in one week, it is assumed that each household faces the (average) prices set by the retailer where they spent most of their budget in that week. Elasticity gaps are generally smaller, especially in the cola system, but with very few exceptions their size is large enough to confirm asymmetry in the same direction as in the other models. Exceptions to this are the own- and cross-price elasticity gaps, which are small and close to zero, for the X-Cola 1lt+ in the cola model, and for fruit & vegetables in the food model.

For the cola model, failure to detect asymmetry might be ascribed to a relatively larger number of missing observations (about 10% of observations), as small and local retailers do not occur in the data enough to estimate prices for all three cola groups. This inconsistency might be explained by the X-Cola 1lt+ being already the category with the lowest number of purchases, and having most of the price information from the largest national retailer with relatively smaller price variation. The same explanation clearly does not hold for fruit & vegetables, and given that the elasticity gap was already quite small in the baseline model, the evidence of asymmetric elasticities for this category is weak.

The effects of adopting different econometric specifications for the demand models can be explored by looking at the elasticity gaps in Tables 8 and 9. Our baseline model applies the zero expenditure and endogeneity corrections, and does not take into consideration household heterogeneity. Incorporating household demographics as intercept shifters in the demand system specification (Model 1) does not produce any appreciable

[7]The complete sets of elasticities are provided as additional on-line material

Table 5. Cross-price Elasticities.

	Symmetric	Reference Price: Lagged Price Loss	Lagged Price Gain	Adaptive Expectation Loss	Adaptive Expectation Gain	Lagged Price (5% trim) Loss	Lagged Price (5% trim) Gain
Cola model							
Price of X-Cola (1lt+)							
X-Cola (other)	0.036	0.069	0.020	0.076	0.016	0.067	0.021
	(0.013)	(0.015)	(0.014)	(0.016)	(0.015)	(0.015)	(0.014)
Other brands	−0.050	0.000	−0.119	0.008	−0.129	−0.004	−0.115
	(0.013)	(0.016)	(0.014)	(0.017)	(0.015)	(0.016)	(0.014)
Price of X-Cola (others)							
X-Cola (1lt+)	−0.081	−0.047	−0.099	−0.040	−0.103	−0.048	−0.098
	(0.011)	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)	(0.012)
Other brands	0.498	0.658	0.095	0.674	0.012	0.635	0.116
	(0.042)	(0.039)	(0.040)	(0.037)	(0.048)	(0.037)	(0.039)
Price of Other Brands							
X-Cola (1lt+)	0.073	0.127	−0.001	0.136	−0.012	0.123	0.002
	(0.012)	(0.015)	(0.014)	(0.015)	(0.015)	(0.014)	(0.014)
X-Cola (other)	0.049	0.211	−0.363	0.226	−0.450	0.187	−0.343
	(0.044)	(0.042)	(0.042)	(0.042)	(0.049)	(0.041)	(0.041)
Food model							
Price of Fruit & Veg							
Snacks	−0.063	−0.103	0.027	−0.123	0.031	−0.026	0.034
	(0.021)	(0.033)	(0.033)	(0.033)	(0.034)	(0.018)	(0.018)
Soft drinks	0.251	0.229	0.084	0.225	0.005	0.143	0.068
	(0.017)	(0.027)	(0.032)	(0.030)	(0.031)	(0.014)	(0.014)
Other foods	0.056	0.049	0.031	0.047	0.016	0.043	0.031
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)
Price of Snacks							
Fruit & Veg	−0.027	−0.044	0.005	−0.052	0.007	−0.017	0.006
	(0.008)	(0.013)	(0.013)	(0.012)	(0.013)	(0.007)	(0.007)
Soft drinks	−0.033	0.029	−0.116	0.058	−0.122	−0.007	−0.131
	(0.020)	(0.023)	(0.023)	(0.024)	(0.022)	(0.016)	(0.016)
Other foods	0.008	0.009	0.003	0.008	0.004	0.005	0.003
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Price of Soft drinks							
Fruit & Veg	0.127	0.118	0.045	0.116	0.004	0.077	0.039
	(0.009)	(0.014)	(0.016)	(0.015)	(0.016)	(0.007)	(0.007)
Snacks	−0.038	0.044	−0.150	0.082	−0.159	−0.001	−0.167
	(0.027)	(0.031)	(0.031)	(0.032)	(0.030)	(0.022)	(0.022)
Other foods	−0.018	−0.019	−0.005	−0.017	0.000	−0.012	−0.005
	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)	(0.001)	(0.001)
Price of Other foods							
Fruit & Veg	0.147	0.117	0.032	0.112	−0.033	0.094	0.039
	(0.012)	(0.015)	(0.017)	(0.014)	(0.015)	(0.007)	(0.007)
Snacks	0.225	0.242	0.169	0.235	0.183	0.262	0.234
	(0.018)	(0.027)	(0.028)	(0.025)	(0.032)	(0.013)	(0.013)
Soft drinks	−0.281	−0.282	−0.156	−0.276	−0.119	−0.288	−0.225
	(0.015)	(0.023)	(0.022)	(0.024)	(0.024)	(0.010)	(0.010)

Note: Standard errors in parentheses. All standard errors are clustered by postcode area (110 postcode areas).

Table 6. Elasticity Gaps and Reference Price Definitions: Cola Model.

	Baseline	(1)	Model (2)	(3)	(4)
			X-Cola (1lt+)		
Own-price	−0.181***	−0.212***	−0.170***	−0.202***	−0.037**
	(0.020)	(0.020)	(0.019)	(0.021)	(0.017)
X-Cola (other)	0.049***	0.060***	0.046***	0.057***	0.052***
	(0.018)	(0.019)	(0.017)	(0.020)	(0.016)
Other brands	0.118***	0.137***	0.111***	0.130***	−0.017
	(0.020)	(0.022)	(0.019)	(0.021)	(0.013)
			X-Cola (others)		
Own-price	−0.623***	−0.735***	−0.576***	−0.797***	−0.184***
	(0.049)	(0.059)	(0.047)	(0.066)	(0.036)
X-Cola (1lt+)	0.052***	0.063***	0.049***	0.061***	0.055***
	(0.020)	(0.021)	(0.018)	(0.021)	(0.017)
Other brands	0.563***	0.663***	0.519***	0.726***	0.133***
	(0.052)	(0.062)	(0.050)	(0.065)	(0.031)
			Other brands		
Own-price	−0.681***	−0.800***	−0.631***	−0.856***	−0.116***
	(0.060)	(0.070)	(0.057)	(0.070)	(0.033)
X-Cola (1lt+)	0.128***	0.149***	0.121***	0.141***	−0.018
	(0.022)	(0.023)	(0.020)	(0.023)	(0.013)
X-Cola (other)	0.574***	0.676***	0.529***	0.739***	0.132***
	(0.053)	(0.063)	(0.051)	(0.067)	(0.031)
Obs.	399,980	400,437	399,980	399,980	359,167
RMSE	0.359	0.359	0.359	0.359	0.359

Notes: $^{***}p < 0.01;^{***}p < 0.05;^{***}p < 0.10$. Elasticity gap figures in the table are the difference between elasticities above and below the reference price (RP). Standard errors in parentheses (Delta Method). Reference prices in the models are as follows:
Baseline model: Lagged geographical price (average by postcode area).
Model (1): Adaptive expectations based on five lags of geographical prices.
Model (2): Lagged geographical price with a 5% trim (prices are considered as different from the RP only when their percent difference is above 5%).
Model (3): Lagged geographical price with a Deaton-type correction.
Model (4): Lagged supermarket price (average across prices of the same outlet across the country)

Table 7. Elasticity Gaps and Reference Price Definitions: Food Model.

			Model		
	Baseline	(1)	(2)	(3)	(4)
			Fruit & Veg		
Own-price	−0.109***	−0.198***	−0.070***	−0.167***	0.014
	(0.034)	(0.030)	(0.015)	(0.037)	(0.009)
Snacks	−0.130**	−0.154**	−0.060**	−0.069	−0.078***
	(0.054)	(0.046)	(0.027)	(0.053)	(0.016)
Soft drinks	0.144***	0.220***	0.075***	0.173***	0.055***
	(0.051)	(0.036)	(0.021)	(0.050)	(0.014)
Other foods	0.018***	0.031***	0.012***	0.023***	−0.003***
	(0.005)	(0.004)	(0.002)	(0.005)	(0.001)
			Snacks		
Own-price	−0.138***	−0.139***	−0.133***	−0.139***	−0.171***
	(0.042)	(0.048)	(0.034)	(0.042)	(0.027)
Fruit & Veg	−0.049**	−0.059**	−0.023**	−0.026	−0.029***
	(0.020)	(0.028)	(0.010)	(0.020)	(0.006)
Soft drinks	0.145***	0.180***	0.124***	0.147***	0.154***
	(0.032)	(0.043)	(0.025)	(0.035)	(0.021)
Other foods	0.006*	0.004	0.002	0.001	0.003**
	(0.003)	(0.004)	(0.002)	(0.003)	(0.001)
			Soft drinks		
Own-price	−0.163***	−0.244***	−0.135***	−0.181***	−0.177***
	(0.040)	(0.040)	(0.030)	(0.046)	(0.027)
Fruit & Veg	0.073***	0.112***	0.038***	0.088***	0.028***
	(0.026)	(0.021)	(0.011)	(0.025)	(0.007)
Snacks	0.194***	0.241***	0.166***	0.197***	0.207***
	(0.043)	(0.046)	(0.033)	(0.047)	(0.028)
Other foods	−0.014***	−0.017***	−0.007***	−0.015***	−0.004**
	(0.004)	(0.004)	(0.002)	(0.004)	(0.001)
			Other foods		
Own-price	−0.011***	−0.018***	−0.007***	−0.008**	0.003**
	(0.004)	(0.004)	(0.002)	(0.004)	(0.001)
Fruit & Veg	0.085***	0.145**	0.055***	0.105***	−0.012**
	(0.023)	(0.059)	(0.010)	(0.024)	(0.006)
Snacks	0.073*	0.052	0.027	0.011	0.042***
	(0.041)	(0.054)	(0.019)	(0.039)	(0.013)
Soft drinks	−0.126	−0.156***	−0.063***	−0.139***	−0.033**
	(0.036)	(0.004)	(0.014)	(0.036)	(0.013)
Obs.	2,055,685	2,055,674	2,055,686	2,055,685	2,052,247
RMSE	0.126	0.127	0.126	0.126	0.126

Notes: $^{***}p < 0.01;^{***} p < 0.05;^{***} p < 0.10$. Elasticity gap figures in the table are the difference between elasticities above and below the reference price (RP). Standard errors in parentheses (Delta Method). Reference prices in the models are as follows:
Baseline model: Lagged geographical price (average by postcode area).
Model (1): Adaptive expectations based on five lags of geographical prices.
Model (2): Lagged geographical price with a 5% trim (prices are considered as different from the RP only when their percent difference is above 5%).
Model (3): Lagged geographical price with a Deaton-type correction.
Model (4): Lagged supermarket price (average across prices of the same outlet across the country)

change in the elasticity gap, and the goodness-of-fit is slightly worse for both the cola and food models. Model 2 presents estimates where endogeneity of total expenditure is not addressed, and the total expenditure enters the model without any instrumenting. Although elasticity gaps are slightly smaller when endogeneity is ignored, the evidence of asymmetry remains clear and consistent with the previous models.

The third alternative specification (Model 3) refers to a model where no correction for zero expenditure is introduced, and all zero expenditures enter the model. This has a large effect on the elasticity gaps for those goods whose proportion of non-purchases is higher, hence the cola model, and snacks and soft drinks in the food model. However, the direction of the bias is towards making the asymmetry larger, which suggests the zero expenditure correction is not generating the asymmetry, but rather reduces it.

Model 4 introduces fixed household effects which are incompatible with the adjustment for zero expenditure and hence Model 3 provides a more natural benchmark to assess the elasticity gaps of the fixed effect model. Once household heterogeneity is accounted for we still find good evidence of asymmetric elasticities for most goods but the asymmetry becomes slightly weaker. This result may be related to the introduction of a large number of household effects (approximately 24,000 and 30,000 in cola and food system, respectively). These are likely to capture most of the price variability, which is already restricted by the number of number of postcode areas (110) and weeks (104). Indeed, the price variability, as measured by the standard deviations, is very small. Coefficients of variation computed from Table 2 range between 14% and 15% for the cola categories, and between 6% and 10% for the food categories. The biggest effect is on the fruit & vegetables category, where asymmetry disappears, suggesting again that household consumption response for this aggregated category is likely to be symmetric. Aggregation of a large number of quite heterogeneous products, and the relative ease to adjust consumption when quantities on sale are continuous, as it is the case for fresh foods, are both plausible justifications for symmetric elasticities for fruit & vegetables.

On balance, our robustness checks confirm the evidence for asymmetric elasticities. Alternative definitions of the reference price had little impact on the size of these gaps. Instead, different econometric specifications do generate conspicuous differences in the elasticity gaps, especially when ignoring the zero expenditure bias, and when introducing fixed household effects. Not all goods are affected to the same extent by the asymmetry, which is likely to be related to the aggregation level and on whether the products are sold in continuous or discrete quantities. The largest asymmetries were found for colas, but this is also due to the fact that price variations are larger for these goods in comparison to the relatively aggregated four food groups. When considering the latter, we provide evidence of a relevant reference price effect for snacks and soft drinks, whereas the evidence is much weaker for fruit & vegetables and no asymmetry is detected for the residual food category.

B. Asymmetric elasticities and simulations

The elasticity gaps we estimated were in some cases relatively large and now we analyse the implications of ignoring these in demand simulations. A basic, but informative as-

Table 8. Elasticity Gaps and Model Specification: Cola Model.

	Model				
	Baseline	(1)	(2)	(3)	(4)
	X-Cola (1lt+)				
Own-price	−0.181***	−0.172***	−0.178***	−1.295***	−0.357***
	(0.020)	(0.020)	(0.020)	(0.114)	(0.047)
X-Cola (other)	0.049***	0.051***	0.072***	0.128***	0.098***
	(0.018)	(0.018)	(0.019)	(0.026)	(0.011)
Other brands	0.118***	0.108***	0.094***	0.145***	−0.003
	(0.020)	(0.019)	(0.020)	(0.023)	(0.009)
	X-Cola (others)				
Own-price	−0.623***	−0.576***	−0.534***	−0.793***	−0.125***
	(0.049)	(0.044)	(0.046)	(0.047)	(0.022)
X-Cola (1lt+)	0.052***	0.055***	0.077***	0.494***	0.376***
	(0.020)	(0.019)	(0.020)	(0.102)	(0.043)
Other brands	0.563***	0.515***	0.453***	0.464***	0.019
	(0.052)	(0.046)	(0.049)	(0.033)	(0.013)
	Other brands				
Own-price	−0.681***	−0.623***	−0.547***	−0.609***	−0.016
	(0.060)	(0.054)	(0.057)	(0.043)	(0.016)
X-Cola (1lt+)	0.128***	0.117***	0.101***	0.801***	−0.018
	(0.022)	(0.021)	(0.022)	(0.128)	(0.047)
X-Cola (other)	0.574***	0.525***	0.462***	0.664***	0.027
	(0.053)	(0.047)	(0.049)	(0.048)	(0.019)
Obs.	399,980	399,980	399,980	420,770	420,770
RMSE	0.359	0.361	0.346	0.372	0.278

Notes: $^{***}p < 0.01$;$^{***}p < 0.05$;$^{***}p < 0.10$. Elasticity gap figures in the table are the difference between elasticities above and below the reference price (RP). Standard errors in parentheses (Delta Method). Model specifications are as follows:
Baseline model: corrected for endogeneity and zero expenditure.
Model (1): Includes household demographics.
Model (2): No endogeneity correction.
Model (3): No correction for zero expenditures.
Model (4): Includes fixed household effects, linear model, no correction for zero expenditures.

Table 9. Elasticity Gaps and Model Specification: Food Model.

	Model				
	Baseline	(1)	(2)	(3)	(4)
			Fruit & Veg		
Own-price	−0.109***	−0.101	−0.094***	−0.040	0.103***
	(0.034)	(0.066)	(0.034)	(0.031)	(0.037)
Snacks	−0.130**	−0.060	−0.136**	1.395***	0.004
	(0.054)	(0.069)	(0.053)	(0.085)	(0.064)
Soft drinks	0.144***	0.129*	0.141***	0.370***	0.004
	(0.051)	(0.068)	(0.050)	(0.079)	(0.056)
Other foods	0.018***	0.013	0.016***	−0.169***	−0.020***
	(0.005)	(0.009)	(0.005)	(0.006)	(0.007)
			Snacks		
Own-price	−0.138***	−0.144**	−0.125***	−0.787***	−0.189***
	(0.042)	(0.072)	(0.043)	(0.087)	(0.069)
Fruit & Veg	−0.049**	−0.023	−0.052**	0.055	0.001
	(0.020)	(0.026)	(0.020)	(0.046)	(0.013)
Soft drinks	0.145***	0.124***	0.144***	1.138***	0.050
	(0.032)	(0.044)	(0.033)	(0.088)	(0.034)
Other foods	0.006*	0.003	0.006	0.020*	0.004
	(0.003)	(0.004)	(0.003)	(0.010)	(0.003)
			Soft drinks		
Own-price	−0.163***	−0.139***	−0.161***	−0.516***	−0.133***
	(0.040)	(0.050)	(0.041)	(0.009)	(0.048)
Fruit & Veg	0.073**	0.065*	0.071**	0.560***	0.001
	(0.026)	(0.034)	(0.026)	(0.091)	(0.019)
Snacks	0.194***	0.167***	0.193***	−0.431***	0.085
	(0.043)	(0.059)	(0.044)	(0.091)	(0.057)
Other foods	−0.014***	−0.013***	−0.014***	0.001	0.005
	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)
			Other foods		
Own-price	−0.011***	−0.003	−0.008**	−0.095***	0.011
	(0.004)	(0.007)	(0.004)	(0.004)	(0.009)
Fruit & Veg	0.085***	0.059	0.074***	−0.471***	−0.105***
	(0.023)	(0.043)	(0.022)	(0.086)	(0.036)
Snacks	0.073*	0.037	0.068	−0.455***	0.100
	(0.041)	(0.046)	(0.041)	(0.050)	(0.075)
Soft drinks	−0.126***	−0.114***	−0.124***	−0.286***	0.079
	(0.036)	(0.043)	(0.034)	(0.003)	(0.073)
Obs.	2,055,685	1,918,544	2,055,685	2,157,537	2,157,537
RMSE	0.126	0.104	0.126	0.089	0.089

Notes: $^{***}p < 0.01$;$^{***}p < 0.05$;$^{***}p < 0.10$. Elasticity gap figures in the table are the difference between elasticities above and below the reference price (RP). Standard errors in parentheses (Delta Method). Model specifications are as follows:
Baseline model: corrected for endogeneity and zero expenditure.
Model (1): Includes household demographics.
Model (2): No endogeneity correction.
Model (3): No correction for zero expenditures.
Model (4): Includes fixed household effects, linear model, no correction for zero expenditures.

sessment can be based on the straightforward application of the estimated asymmetric elasticities, using the Delta method to obtain standard errors. Table 10 provides some examples of how elasticity-based simulations change when reference prices are considered, and asymmetry is allowed for, based on our baseline model.

To this purpose we consider four basic scenarios of price change. For the cola market, we assess the effects on demand from a 10% price increase in all X-Colas, and the effects of a 10% price cut in the price set by competitors. For the food model, we explore the consumption effects of hypothetical fiscal measures to promote healthier consumption, such as a 10% increase in the price of snacks, which might be induced by a tax targeting less healthier products, and a 10% decrease in the price of fruit & vegetables, to simulate a subsidy on healthier products.

The effects of a 10% rise in X-Cola prices are underestimated by the symmetric model, as loss aversion is ignored. Considering all three categories in the system, the bias is not trivial, as purchased quantities for bottled X-Cola fall by a further 0.6% relative to the symmetric model. Sales of all other X-Cola products are also simulated to be lower by 1.6% if asymmetry is allowed. Substitution to competitor brands increases by 6.6% instead of 4.5%, as predicted by the symmetric model. While trivial differences at small scale, a rough back-of-the-envelope estimation to scale up consumption response taking into account the number of British households helps appreciating the magnitude of these differences. In comparison to the symmetric model, allowing for asymmetries estimates an additional reduction of more than 100,000lt per week of X-Cola sold in Great Britain, and an additional increase of 300,000lt sold by competitors per week.

On the other hand, the symmetric model overestimates the response to a 10% decrease in the price set by competitors of X-Cola. The demand for colas of other brands increases by 6.4%, rather than 11.1% as predicted by the symmetric model, a difference of about 700,000lt per week when average household responses are projected at the national level. In addition, the asymmetric model predicts that X-Cola purchases also increase by 350,000lt per week in response to the price cut, while simulations from the symmetric model see a substitution effects which would reduce purchases by around 50,000lt per week.

Similar considerations apply to the food model, but to a lesser extent, as the estimated asymmetries are smaller. As before, the symmetric model underestimates the effects of a loss induced by taxation. Reduction in snack consumption in response to the 10% tax is -9.8% according to the symmetric model, and -10.5% according to the asymmetric model. In terms of quantities this means a little more than one gram per household per week. It should be noted, however, that according to the symmetric model such a tax would also lead to a reduction in the demand for soft drinks (-0.3%), whereas the asymmetric model predicts a +0.3% increase in soft drink consumption.

As before, subsidies - hence consumer gains - are estimated to have a relatively smaller impact on consumption. Still, the difference which emerges from our baseline model relative to the symmetric model is meaningful. The symmetric model simulates an increase in consumption of fruit & vegetables of 0.531Kg per household per week, in comparison to 0.457Kg predicted by the baseline model, which means a distance of almost a portion per household per week. However, the asymmetry for this category is not as robust to alternative model specifications. Considering the impact on snack consumption, the two models provide simulations with opposite signs. The symmetric model predicts substitution to snacks when fruits & vegetables prices are subsidized, whereas the asymmetric effects suggest a complementary effect, and predict a small reduction in snack consumption. A reduction in soft drink demand due to subsidies on fruit & vegetables is also overestimated by the asymmetric model (2.5% relative to the 0.8% predicted by the asymmetric model).

VI. Summary and Conclusion

This paper extends the Almost Ideal Demand System specification to incorporate reference prices and allow for asymmetric consumer response depending on whether price changes occur above or below the reference price. Importantly, we generalize previous efforts by incorporating cross-price reference effects allowing estimation of asymmetric cross-price elasticities, consistent with the requirements of consumer theory.

We test this theoretical advancement by extending the functional form of the Almost Ideal Demand System to allow for reference prices, and we exploit a large data-set based on home scan data to test the empirical evidence on asymmetric elasticities. We find good evidence of asymmetric own-price and cross-price elasticities, which is quite robust to changes in the definition of reference prices. In our baseline we opted for using the lagged price as the reference which has the attractiveness of straightforward interpretation of the elasticities, as losses correspond to all situations when price has increased since last shopping, and gains refer to a price decrease.

We also checked the sensitivity of our asymmetric estimates to various econometric specifications which are known to influence estimates of demand models. Controlling for endogeneity of total expenditure, or adjustment for the unit value quality component does not affect estimates, whereas correcting for zero expenditure does change both the elasticity values and the size of asymmetry, but in the direction of detecting smaller asymmetries relative to the model without zero correction. Furthermore, the censored model controls for possible stockpiling in the first stage decision to purchase. When fixed household effects are introduced, the asymmetries become smaller, particularly for fruits & vegetables.

Our empirical tests on demand models augmented with internal reference prices lead us to two main considerations on the nature of asymmetric elasticities. First, we find that the relevance of asymmetry increases with the level of product detail. The larger the number of products aggregated into a single category, the smaller the evidence of asymmetry, to the point that no asymmetry emerges when considering large food aggregates. Not unrelated to the aggregation aspect, asymmetry appears smaller when consumers have more flexibility in choosing purchasing quantities. Products sold in discrete quantities and set packages, such as cola bottles, are more likely to exhibit asymmetric elasticities relative to goods like fruit & vegetables, often sold loosely, which means that it is easier to adjust the purchased quantities if price changes.

Second, we bring further evidence on consumer loss aversion. Consumers show a

Table 10. Simulated Effects of Price Policies on Purchased Quantities with Asymmetric Elasticities.

	Model	
	Symmetric	Asymmetric (Baseline)
Cola Model		
	10% Increase in all X-Cola Prices	
X-Cola (1lt+)		
	-10.66^{***}	-11.20^{***}
	(0.13)	(0.15)
X-Cola (other)	-13.95^{***}	-15.58^{***}
	(0.42)	(0.39)
Other brands	$+4.48^{***}$	$+6.58^{***}$
	(0.46)	(0.43)
	10% Cut in Prices of Competitors	
X-Cola (1lt+)	-0.73^{***}	$+0.01$
	(0.12)	(0.14)
X-Cola (other)	-0.49	$+3.63^{***}$
	(0.44)	(0.42)
Other brands	$+11.15^{***}$	$+6.42^{***}$
	(0.46)	(0.46)
Food Model		
	10% Tax on Snacks	
Fruit & Veg	-0.28^{***}	-0.32^{**}
	(0.08)	(0.13)
Snacks	-9.76^{***}	-10.50^{***}
	(0.28)	(0.36)
Soft drinks	-0.33	$+0.43^{*}$
	(0.20)	(0.25)
Other foods	$+0.04^{***}$	$+0.06^{**}$
	(0.01)	(0.02)
	10% Subsidy on Fruit and Vegetables	
Fruit & Veg	$+13.66^{***}$	$+11.76^{***}$
	(0.14)	(0.23)
Snacks	$+0.59^{**}$	-0.49
	(0.21)	(0.34)
Soft drinks	-2.48^{***}	-0.86^{***}
	(0.17)	(0.32)
Other foods	-0.32^{***}	-0.25^{***}
	(0.01)	(0.03)

Note: $^{***}p < 0.01$;$^{***}p < 0.05$;$^{***}p < 0.10$. Figures show the percent change in purchased quantities under the different pricing scenarios. Standard errors in brackets (Delta method).

stronger reaction to price increases relative to price reductions, and importantly our complete demand system specification enables us to generalize this result to substitution effects. Our model shows that substitution elasticities are larger when the current price exceeds the reference price, and in a number of cases we even find that two goods that are substitutes in case of a price increase become complements if price decreases. Given that we are referring to Marshallian elasticities, incorporating expenditure effects, this looks like a plausible behaviour, hidden behind substitution elasticities close to zero in models without reference prices.

Our basic simulations showed that the bias from ignoring asymmetric consumption response may be substantial and that the extension is especially desirable when demand models are used to develop pricing strategies or fiscal policies. With the availability of a large and highly detailed data-set as our home scan data, generalizing demand models to allow for a reference price effect in both own- and cross-prices comes at almost no computing cost, and the case of symmetric elasticities can be simply regarded as a special case.

References

Bidwell Jr, M. O., Wang, B. X., and Zona, J. D. (1995). An analysis of asymmetric demand response to price changes: The case of local telephone calls. *Journal of Regulatory Economics*, 8(3):285–298.

Blundell, R. (1988). Consumer behaviour: Theory and empirical evidence–a survey. *The Economic Journal*, 98(389):16.

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

Deaton, A. and Muellbauer, J. (1980). An almost ideal demand system. *The American Economic Review*, 70(3):312–326.

Dossche, M., Heylen, F., and Van den Poel, D. (2010). The kinked demand curve and price rigidity: Evidence from scanner data. *The Scandinavian Journal of Economics*, 112(4):723–752.

Drakopoulos, S. A. (1992). Psychological thresholds, demand and price rigidity. *The Manchester School*, 60(2):152–168.

Farrell, M. J. (1952). Irreversible demand functions. *Econometrica*, 20(2):171–186.

Gately, D. (1992). Imperfect price-reversibility of us gasoline demand: asymmetric responses to price increases and declines. *The Energy Journal*, 13(4):179–207.

Haavelmo, T. (1944). The probability approach in econometrics. *Econometrica*, 12(Supplement):iii–115.

Heidhues, P. and Kőszegi, B. (2008). Competition and price variation when consumers are loss averse. *The American Economic Review*, 98(4):1245–1268.

Kahneman, D. and Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, 47(2):263–291.

Kalwani, M. U., Yim, C. K., Rinne, H. J., and Sugita, Y. (1990). A price expectations model of customer brand choice. *Journal of Marketing Research*, 27(3):251–262.

Kalyanaram, G. and Winer, R. S. (1995). Empirical generalizations from reference price research. *Marketing Science*, 14(3):G161-G169.

Marshall, A. (1920). *Principles of economics: An introductory volume*. Macmillan London.

Mazumdar, T., Raj, S., and Sinha, I. (2005). Reference price research: Review and propositions. *Journal of Marketing*, 69(4):84–102.

Meyer, R. and Johnson, E. J. (1995). Empirical generalizations in the modeling of consumer choice. *Marketing Science*, 14(3):G180–G189.

Mighell, R. and Allen, R. (1939). Demand schedules - "normal" and "instantaneous". *Journal of Farm Economics*, 21(3):555–569.

Muth, J. F. (1961). Rational expectations and the theory of price movements. *Econometrica*, 29(3):315–335.

Nakamura, R., Suhrcke, M., Jebb, S. A., Pechey, R., Almiron-Roig, E., and Marteau, T. M. (2015). Price promotions on healthier compared with less healthy foods: a hierarchical regression analysis of the impact on sales and social patterning of responses to promotions in Great Britain. *American Journal of Clinical Nutrition*, 101(4):808–816.

Nerlove, M. (1958). Adaptive expectations and cobweb phenomena. *The Quarterly Journal of Economics*, 72(2):227–240.

Putler, D. S. (1992). Incorporating reference price effects into a theory of consumer choice. *Marketing science*, 11(3):287–309.

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

Tauchmann, H. (2005). Efficiency of two-step estimators for censored systems of equations: Shonkwiler and yen reconsidered. *Applied Economics*, 37(4):367–374.

Winer, R. S. (1986). A reference price model of brand choice for frequently purchased products. *Journal of Consumer Research*, 13(2):250–256.

Working, E. (1932). Indications of changes in the demand for agricultural products. *Journal of Farm Economics*, 14(2):239–256.

A Appendix

A. Generalized Slutsky Equation

Because demand schedules are allowed to adapt, the total effect of a price change is captured by the total derivative of the Marshallian demand function f. Considering the impact of a change in price p_j on the demanded quantity q_i, optimization implies that $q_i = h(\mathbf{p}, \mathbf{r}, u) = \mathbf{q} = f(\mathbf{p}, \mathbf{r}, x)$, so that:

$$\frac{df_i(\mathbf{p}, \mathbf{r}, x)}{dp_j} = \frac{dh_i(\mathbf{p}, \mathbf{r}, u)}{dp_j} = \frac{\partial f_i}{\partial p_j} + \frac{\partial f_i}{\partial E}\frac{dE}{dp_j} \tag{18}$$

where $\mathbf{p}$ is the vector of prices, $\mathbf{r}$ is the vector of reference prices, u is the utility level, x is the available budget, h is the Hicksian demand function, E is the expenditure function and

$$\frac{dE}{dp_j} = \frac{\partial E}{\partial p_j} + \sum_i I_i \frac{\partial E}{\partial l_i}\frac{dl_i}{dp_j} + \sum_i (1 - I_i)\frac{\partial E}{\partial g_i}\frac{dg_i}{dp_j}$$

Since

$$\frac{dl_i}{dp_j} = \frac{dg_i}{dp_j} = 0 \qquad \forall i \neq j$$

the relationship simplifies to:

$$\begin{aligned}
\frac{dE}{dp_j} &= \frac{\partial E}{\partial p_j} + I_j \frac{\partial E}{\partial l_j}\frac{dl_j}{dp_j} + (1 - I_j)\frac{\partial E}{\partial g_j}\frac{dg_j}{dp_j} \\
&= \frac{\partial E}{\partial p_j} + I_j \frac{\partial E}{\partial l_j}\frac{d(p_j - r_j)}{dp_j} + (1 - I_j)\frac{\partial E}{\partial g_j}\frac{d(r_j - p_j)}{dp_j} \\
&= \frac{\partial E}{\partial p_j} + I_j \frac{\partial E}{\partial l_j} - (1 - I_j)\frac{\partial E}{\partial g_j}
\end{aligned}$$

Which simply implies that the impact of losses (gains) on total cost must be added (subtracted) to the usual effect of a price change when minimising the cost function. This ensures duality with the utility maximisation problem, based on the augmented utility function incorporating gains and losses.

Shephard's Lemma can be also generalised to show[8] that:

$$\frac{\partial E}{\partial p_j} = h_j[\mathbf{p}, I \circ (\mathbf{p} - \mathbf{r}), (1 - \mathbf{I}) \circ (\mathbf{r} - \mathbf{p}), u]$$

[8] Demonstration is provided in Putler (1992), page 305

Thus (18) becomes:

$$\begin{aligned}\frac{dh_i(\mathbf{p},\mathbf{r},U)}{dp_j} &= \frac{\partial f_i}{\partial p_j} + \frac{\partial f_i}{\partial E}\left[\frac{\partial E}{\partial p_j} + I_j\frac{\partial E}{\partial l_j} - (1-I_j)\frac{\partial E}{\partial g_j}\right] = \\ &= \frac{\partial f_i}{\partial p_j} + \frac{\partial f_i}{\partial E}\left[h_j + I_j\frac{\partial E}{\partial l_j} - (1-I_j)\frac{\partial E}{\partial g_j}\right] = \\ &= \frac{\partial f_i}{\partial p_j} + h_j\frac{\partial f_i}{\partial E} + \frac{\partial f_i}{\partial E}\left[I_j\frac{\partial E}{\partial l_j} - (1-I_j)\frac{\partial E}{\partial g_j}\right]\end{aligned}$$

Since optimal consumption $q_j = h_j[\mathbf{p},\mathbf{r},U] = f_j[\mathbf{p},\mathbf{r},M]$, after rearranging terms, the generalised Slutsky equation can written as

$$\begin{aligned}\frac{\partial f_i(\mathbf{p},\mathbf{r},x)}{\partial p_j} &= \frac{dh_i(\mathbf{p},\mathbf{r},u)}{dp_j} - q_j\frac{\partial f_i(\mathbf{p},\mathbf{r},x)}{\partial E} \\ &\quad + \frac{\partial f_i(\mathbf{p},\mathbf{r},x)}{\partial E}\left[(1-I_j)\frac{\partial E}{\partial g_j} - I_j\frac{\partial E}{\partial l_j}\right]\end{aligned}$$