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Between preferences and references: Asymmetric price elasticities and the simulation of fiscal policies

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Abstract

Canonical demand studies and fiscal policy simulations rest on the assumption that consumers react symmetrically to price increases and decreases. Such assumption has been challenged from both the empirical and theoretical points of view. We propose theoretically consistent empirical specifications to estimate discrete choice models (random utility DCM) and continuous demand systems (EASI and AIDS demand systems) that allow for reference prices and asymmetric own and cross-price demand response. Our application focuses on the demand for sugar-sweetened beverages in Great Britain, using transaction-level household purchase data and different product aggregation levels. We find substantial evidence of asymmetric consumer response and loss aversion, with a stronger response when prices rise above their reference level. Our results holds for both DCMs on highly differentiated products and demand systems on aggregate product categories, and are robust to alternative model and reference price specifications. Simulations of taxes and subsidies on soft drinks shows that ignoring asymmetry may lead to biases, especially when predicting price cuts.

JEL: D11, D12, H31, L66, Q18

Keywords: Reference Price, Price Elasticities, Demand Models, Soft Drinks, Loss Aversion

Highlights

- There is evidence that consumer do not react symmetrically to price rises and cuts
- Ignoring asymmetric price elasticities may lead to biases when simulating fiscal measures
- We specify a discrete choice model and an EASI demand system with reference prices
- Using home scan data, we find evidence of asymmetric elasticities in soft drink demand
- Ignoring loss aversion may bias simulation of fiscal measures, especially subsidies

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Abstract

Canonical demand studies and fiscal policy simulations rest on the assumption that consumers react symmetrically to price increases and decreases. Such assumption has been challenged from both the empirical and theoretical points of view. We propose theoretically consistent empirical specifications to estimate discrete choice models (random utility DCM) and continuous demand systems (EASI and AIDS demand systems) that allow for reference prices and asymmetric own and cross-price demand response. Our application focuses on the demand for sugar-sweetened beverages in Great Britain, using transaction-level household purchase data and different product aggregation levels. We find substantial evidence of asymmetric consumer response and loss aversion, with a stronger response when prices rise above their reference level. Our results holds for both DCMs on highly differentiated products and demand systems on aggregate product categories, and are robust to alternative model and reference price specifications. Simulations of taxes and subsidies on soft drinks shows that ignoring asymmetry may lead to biases, especially when predicting price cuts.

1. 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 parameters is estimated, without a distinction between increasing and decreasing prices. This 'symmetry' assumption has been frequently challenged in the marketing and consumer behavior literature as unnecessarily restrictive, and empirical counter-evidence has been provided for several goods including soft drinks, eggs, coffee, yogurt, and peanut butter (Kalyanaram and Winer, 1995).

Recognizing that consumer response may be asymmetric becomes especially relevant when empirical models are used to simulate the effects of private price strategies or product-targeted fiscal measures. Relevant examples are taxes or subsidies designed to influence the healthiness of diets. Most commonly, levies on sugar-sweetened beverages (SSB) have been adopted in many countries across the world in recent years (Grummon et al., 2019). Simulations for this type of taxes mostly rely on elasticity estimates from continuous demand systems (CDS), with relatively aggregate drink categories (e.g. Tiffin et al. 2015; Zhen et al. 2014; Harding and Lovenheim 2017; Caro et al. 2017). More recently, the estimation of discrete choice models (DCM) for differentiated products has gained popularity (Bonnet and Requillart, 2011; Liu et al., 2014; Griffith et al., 2019), also in response to the availability of large transaction-level data-sets based on scan technologies (Griffith and O'Connell, 2009). However, none of these studies predicts demand response while accounting explicitly for asymmetric response to price changes[1].

We explore the effect of extending the DCM and CDS frameworks to account for differential response to price increases and decreases, and focus on an application to soft drinks in Great Britain using transaction-level household scan data. We explicitly frame the proposed empirical models within consumer theory. By comparing the evidence on asymmetric elasticities from DCMs with highly differentiated products and CDS with policy-relevant product categories, we bring new evidence on the effects of product aggregation on demand response asymmetries.

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; Caputo et al., 2018)[2]. 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 tend to react stronger to a price increase, which generates a loss of utility, than to a price decrease leading to an utility gain.

Few studies based on secondary data have estimated demand models with the explicit goal to capture asymmetric response to price changes. The focus of these studies is on single goods and/or brand-level discrete choice models, as in e.g. Kalwani et al. (1990) (ground coffee), Bell and Lattin (2000) (frozen orange juice) Caputo et al. (2018) (milk and ketchup). However, policy simulations require evidence at a higher level of aggregation (e.g. product category) and

[1]An exception is the empirical contribution by Cornelsen et al. (2019), which is based on the estimation of individual empirical demand equations without considering the theoretical underpinnings

[2]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

for a wider set of substitute goods. If one considers taxation of SSBs, the emphasis might be on the substitution between soft drinks high in sugar with those with less sugar, but also between soft drinks and alcoholic drinks, while within category substitutions are less relevant in relation to health outcomes. Under such a perspective, reliable estimates from continuous demand systems based on aggregate categories become useful as an alternative or a complement to DCMs. In the economics literature, some studies have proposed continuous demand functions allowing for asymmetric response to price changes, while considering aggregate categories of goods (e.g. Gately (1992) for US gasoline demand, Bidwell Jr et al. (1995) for telephone calls). However, these studies ignored cross-category substitutions and consumer theory constraints. The most complete theoretical effort towards the specification of a continuous demand model with reference price effects and asymmetric price response is found in Putler (1992). However, to the best of our knowledge, there are no studies that specify a theoretically-consistent CDS[3].

The present study aims to fill this gap in the theoretical and empirical literature, by (a) proposing theoretically valid specifications for both discrete choice models with highly differentiated products (e.g. at the product barcode level), and category-level continuous demand systems incorporating reference price effects; (b) test these models empirically using a highly detailed home scan data-set from the Great Britain (GB) Kantar Fast Moving Consumer Good (FMCG) panel, which collates transaction-level information on drink purchases from more than 30,000 households annually. Our dataset spans over four years between 2012 and 2015. We assess the evidence on asymmetric response to price changes captured at different product aggregation levels, and we check the implications for policy analysis by simulating the effect of different SSB price interventions.

We find marked asymmetries in price elasticities when reference prices are considered in demand models. When lagged prices are used as the reference, demand response to price increases is higher relative to price cuts, consistently with previous evidence on loss aversion. Our results hold with both DCMs on highly differentiated products and CDSs on aggregate categories. Considering these asymmetries has an impact on the simulation of taxes and subsidies, although the difference is relatively small for taxes.

The remainder of this paper is organized as follows. Section 2. elaborates the extension of utility-based demand models to account for reference prices, and proposes augmented specifica-

[3]One partial exception is the study by Dossche et al. (2010), where an Almost Ideal Demand System specification is augmented to allow for nonlinear price effects, but without a theoretical justification. Their empirical application is based on retail sales rather that consumer purchase data

tions for both discrete choice and continuous choice models, based on a mixed logit specification and an EASI demand system specification, respectively. Section 3. illustrates the characteristics and contents of the home scan data-set and shows the results from the empirical applications on SSBs, including robustness checks and simulations exercises. Section 4. concludes.

2. Demand models, reference prices and asymmetric response

Many distinguished attempts exist in the literature to reconcile discrete choice and continuous choice demand models, from Hanemann (1984) to Lewbel and Pendakur (2017). However, the two streams remain distinct in the empirical literature, as the former is preferred within the industrial organization discipline (Nevo, 2011) and marketing (Chintagunta and Nair, 2011) and the latter remains relatively popular in some applied policy fields, e.g. health (Jofre-Bonet and Petry, 2008) energy (Renner et al., 2018) or food (Atkin, 2013). The empirical trade-offs between the two methods are clear, with DCMs being preferred for highly differentiated products and CDSs having more immediate applications when the focus is on substitutions between aggregate categories of goods and often chosen for welfare analysis.

The distinction between DCMs and CDSs begins with a different specification of the utility function. When consumers are assumed to develop preferences on the bundle of available products, the resulting utility depends on the quantity consumed of each of the N products, i.e. $u = f(q_i)$, with $i = 1, 2, ..., N$. Within this framework, consumers choose the quantities that maximize their utility subject to a budget constraint and market prices, and such optimization process implies continuous choices as modelled by demand systems. The alternative model developed by McFadden (1974) considers a product as a combination of different attributes, whose part-worth utilities determine the total level of utility derived from consuming that product. The utility gained from the consumption of a given product i characterised by M different attributes is $u_i = f(x_m)$, where x_m is the level of each attribute and $m = 1, ..., M$. This model explicitly deals with discrete choices, i.e. when confronted with a set of available alternatives, a consumer chooses the option with the highest utility. This implies that the empirical definition of the relevant choice set becomes crucial, as the alternatives must be mutually exclusive and exhaustive. This does not necessarily limit the potential of DCMs and combination of goods may be considered as elements of the choice set. However, it may become unpractical to consider all combinations of highly differentiated products belonging to multiple categories that may be policy relevant, e.g. the sugar-sweetened, diet soft drink categories, water, alcoholic drinks, etc.

Given these empirical trade-offs, here we show how both classes of models can be extended to consider reference prices, hence accounting for explicit loss and gain effects within the utility function.

2.1. Reference prices

The empirical evidence on asymmetric consumer response to price increases and decreases dates back to the mid-last century, in relation to seminal papers on irreversible demand functions[4] (Farrell, 1952; Haavelmo, 1944). Despite robust empirical evidence on asymmetric elasticities and the superior performance of irreversible demand functions, few theoretical justification grounded on consumer behaviour have been provided. These rest largely on Prospect Theory (Kahneman and Tversky, 1979) and Transaction Utility Theory (Thaler, 1985), both widely studied in marketing science, which dictate that when completing a transaction for a good, consumers experience utility losses (gains) when they purchase a good at a price above (below) a given reference price, i.e. an expected or fair price for that good.

Hence, the utility function can be augmented to account for the gains and losses for each good in their basket, i.e. $u = f(q_i, g_i, l_i)$. In the DCM part-worth utility specification gains and losses can be easily be interpreted as additional attributes for each good.

The operationalization of the reference price concept is not immediate and has generated a rich research stream in the marketing literature (Mazumdar et al., 2005). For brand-level choices, reference prices may reflect the consumer-expected price for each brand, an anticipation formed by consumer during an inter-purchase period (Winer, 1986). Reference prices are broadly classified into internal reference prices (IRP) and external reference prices (ERP). According to adaptation-level theory, IRPs are stored in memory and consumers assess new price stimuli (e.g. at the point of purchase) in relation to their prevailing norm, whereas ERPs are based on stimuli observed directly in the purchase environment, e.g. the price of a substitute product on the same shelf (Mayhew and Winer, 1992). In economics, the IRP concept, as discussed later, is based on adaptive rational expectations (Nerlove, 1958), and allows for both estimable irreversible demand functions and asymmetric elasticities, while maintaining consis-

[4] Assume a 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.

tency with the theoretical requirements of demand theory. Reversible demand functions and symmetric elasticities become a special case of this generalized framework where IRPs equal actual prices, i.e. perfect expectations.[5]

A thorough discussion of the extension of the utility framework to accommodate reference prices is provided in in Putler (1992), where loss (l) and gains (g) are defined as 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:

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

Losses and gains are then defined as $l_i = I_i(p_i - r_i)$ and $g_i = (1 - I_i)(r_i - p_i)$, respectively. Gains and losses can enter the utility function under both the DCM and CDS frameworks, and we discuss them separately.

2.2. Discrete choice models with reference prices

The common theoretical framework for the derivation of empirical discrete choice demand models is based on random utility maximization (RUM). Consumers are assumed to choose the alternative that provides the highest utility, where utility is composed of a deterministic component, consisting of the weighted sum of part-worth utilities provided by the product attributes, and a random part. Hence, the expected utility from choosing a given good i can be written as $u_i = \sum_{m=1}^{M} \beta_m x_{im} + \varepsilon_i$, where x_{im} is the level of the attribute m in the alternative i, and β_m captures the contribution of that attribute to total utility. The random vector $\varepsilon_i\ \forall i = 1, \ldots N$ is assumed to be independent and identically distributed (IID) extreme-value. The utility-maximizing consumer chooses the alternative i if $RU_i > RU_j\ \forall j \neq i$.

The parameters of the RUM-based DCM can be estimated by specifying a mixed logit (ML) model with random coefficients, which accounts for taste heterogeneity across consumers (McFadden and Train, 2000). For our empirical specification, we follow Kalwani et al. (1990)

[5] It should be noted here that there are alternative, less researched, explanations for asymmetric elasticities in the marketing literature, as stockpiling, habits and addiction as well as general consumer heterogeneity (Bell and Lattin, 2000; Slonim and Garbarino, 2009). Testing each of these goes beyond the scopes of this study, and we make the choice of the dominant explanation via IRPs. Further research should explore the (additional) effects, if any arise from these alternative sources of asymmetry.

and consider gains and losses as additional product attributes. The (random) utility u_{hi} derived by consumer h when choosing product i over the alternatives in the choice set is specified as follows:

$$u_{hi} = \gamma_h p_{hi} + \delta_h l_{hi} + \omega_h g_{hi} + \beta_{\mathbf{h}} \mathbf{x_i} + \zeta_{\mathbf{i}} \mathbf{z_h} + \varepsilon_{hi} \tag{1}$$

where p_{hi} is the price of product i faced by consumer h, l_{hi} is the loss associated with product i when the price exceeds the consumer reference price; g_{hi} is the gain when the price is below the consumer reference level; $\mathbf{x_i}$ is a vector containing the remaining attribute levels for product i, and z_h is a vector of consumer characteristics. The random coefficients γ_h, δ_h, ω_h and $\beta_{\mathbf{h}}$ are assumed to be normally distributed. Finally, the coefficient vector $\zeta_{\mathbf{i}}$ captures systematic product-specific taste heterogeneity associated with measurable consumer characteristics.

If the error term ε_{hi} is assumed to follow an IID extreme-value distribution, then the probability of choosing i over the set of choices follows the logit formulation, and the likelihood function for (1) across a sample of consumers for a given choice set can be written and maximized via maximum simulated likelihood, with the possibility of allowing for individual multiple and correlated choices observed over time (McFadden and Train, 2000; Hole, 2007).

A likely issue that could arise in the estimation of (1) is the endogeneity of the observed purchase prices. In practice, it is unlikely that all relevant product attributes are observed. When these unobserved attributes influence both prices and utility, estimates are inconsistent. A control function approach can be applied to correct for endogeneity in discrete choice models (Petrin and Train, 2010). This consists of augmenting the model with an additional variable to control for the endogenous component. To this purpose, the error ε_{hi} is split into an exogenous component ϵ_{hi}, and a second component υ_{hi} correlated with prices, $\varepsilon_{hi} = \epsilon_{hi} + \upsilon_{hi}$.

An instrumental variable (IV) procedure is then adopted, where the standard approach relies on contemporary prices for the same products in other locations (Hausman, 1996):

$$p_{hi} = \gamma \mathbf{p^*_{hi}} + \upsilon_{hi} \tag{2}$$

where $\mathbf{p}^*_{hi}$ is a set of instrumental prices that do not enter the utility function directly but are correlated with the price p_{hi}, and υ_{hi} is the unobserved (endogenous) component. As for standard IV methods, a two-stage procedure is then adopted: first, equation (2) is estimated via OLS to obtain the residuals $\hat{\upsilon_{hi}}$; then, these estimates are fed into the DCM model (1) as an additional variable.

2.3. Continuous demand systems with reference prices: the EASI model

The derivation of demand systems with reference prices follows directly from the augmented utility and cost functions as described in Putler (1992). The consumer minimizes the total cost x subject to the utility level defined by the augmented utility function:

$$\min_{\mathbf{q}\geq\mathbf{0}} \quad x = \mathbf{p}'\mathbf{q} \quad \text{subject to} \quad U(\mathbf{q}, \mathbf{l}, \mathbf{g}) \geq u \tag{3}$$

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

$$x = E[\mathbf{p}, \mathbf{I}\circ\mathbf{l}, (\mathbf{1}-\mathbf{I})\circ\mathbf{g}, u] \tag{4}$$

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 follow the usual steps to obtain a system of Marshallian demand functions. The Hicksian demand functions $\mathbf{q} = h(\mathbf{p}, \mathbf{r}, u)$ are obtained via Shephard's Lemma, and the indirect utility function is generated by inverting the expenditure function. The Marshallian demand functions $\mathbf{q} = f(\mathbf{p}, \mathbf{r}, x)$ can be written 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[6]:

$$\frac{\partial f_i(\mathbf{p}, \mathbf{r}, x)}{\partial p_j} = \frac{\mathrm{d}h_i}{\mathrm{d}p_j} + q_j\frac{\partial f_i}{\partial x} + \frac{\partial f_i}{\partial x}\left[(1-I_j)\frac{\partial E}{\partial g_j} - I_j\frac{\partial E}{\partial l_j}\right] \tag{5}$$

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:

[6] See Appendix A1.. The equation generalizes Putler's result to the effect of cross-price changes

$$\frac{\mathrm{d}h_i(\mathbf{p},\mathbf{r},u)}{\mathrm{d}p_j} = \frac{\partial h_i}{\partial p_j} + \sum_{s=1}^{n} \frac{\partial h_i}{\partial l_s}\frac{\mathrm{d}l_s}{\mathrm{d}p_j} + \sum_{s=1}^{n} \frac{\partial h_i}{\partial g_s}\frac{\mathrm{d}g_s}{\mathrm{d}p_j} = \frac{\partial h_i}{\partial p_j} + I_j\frac{\partial h_i}{\partial l_j} - (1-I_j)\frac{\partial h_i}{\partial g_j} \tag{6}$$

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 (6) follows from symmetry of the canonical Slutsky Matrix, which implies that $\frac{\partial h_i}{\partial p_j} = \frac{\partial h_j}{\partial p_i}$. By definition, IRPs based on adaptive expectations are determined before the actual price is observed, i.e. r_i adjust to price changes with (at least) one period delay. Hence, the r_i are pre-determined and 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 $\frac{\partial h_i}{\partial p_j} = \frac{\partial h_j}{\partial p_i}$. This general derivation may be adapted to a variety of empirical demand systems. Here we consider an Exact Affine Stone Index (EASI) demand system with reference prices (Lewbel and Pendakur, 2009), a specification that is especially valuable for our setting as it allows for unobserved taste heterogeneity, just like in the RUM framework used for DCM[7].

The generic equation for an individual good within our extended EASI system is written as follows:

$$\begin{aligned} w_i = &\sum_{j=1}^{N} \gamma_{ij}\log p_j + \sum_{j=1}^{N} \delta_{ij} I_j(\log p_j - \log r_j) \\ &- \sum_{j=1}^{N} \omega_{ij}(1-I_j)(\log r_j - \log p_j) + \zeta_{\mathbf{i}}\mathbf{z} + \sum_{r=0}^{2} \beta_{ir} y^r + \epsilon_i \end{aligned} \tag{7}$$

where w_i is the expenditure share for the i-th good, prices p_j and reference prices r_j for all goods enter the equation in logarithms, and losses and gains are incorporated through the indicator function I_j. As for the DCM model, the vector $\mathbf{z}$ includes measurable consumer characteristics, whereas y is the implicit utility. In the EASI specification (Pendakur, 2009; Lewbel and Pendakur, 2009), implicit utility is the nominal expenditure deflated by an index which is affine to the Stone index, and it follows from a cost function which is quadratic in log prices. The cost function also allows for observed consumer characteristics and unobserved heterogeneity in preferences, the latter is modelled through ϵ_i, i.e. the error terms of the demand

[7] The more traditional flexible functional form of the Almost Ideal Demand System (Deaton and Muellbauer, 1980) can be also easily adapted to consider reference prices as shown in Appendix A3.

equations, that are cost shifters in the cost function. The same cost function can be augmented to account for reference prices (see Appendix A2.), so that the implicit utility has the following specification:

$$
\begin{aligned}
y = u = & \log x - \sum_{j=1}^{N} w_j \log p_j + 0.5 \sum_{j=1}^{N} \sum_{k=1}^{N} \gamma_{jk} \log p_j \log p_k \\
& + 0.5 \sum_{j=1}^{N} \sum_{k=1}^{N} \delta_{jk} I_j (\log p_j - \log r_j)(\log p_k - \log r_k) \\
& - 0.5 \sum_{j=1}^{N} \sum_{k=1}^{N} \omega_{jk} (1 - I_j)(\log r_j - \log p_j)(\log r_k - \log p_k)
\end{aligned} \tag{8}
$$

The EASI "implicit" Marshallian demand system with reference prices described by (7) and (8) also allows for nonlinear Engel curves, and we adopt a quadratic form. The empirical model can be estimated via the iterative linear procedure described in Pendakur (2009), which rests on an IV approach to address the endogeneity of y. Furthermore, prices may be treated as endogenous by instrumenting them with prices in other locations, as described for the DCM case. The EASI parameters are subject to the adding-up, homogeneity and symmetry requirements, which implies additional constraints on the loss and gain coefficients (see Appendix A2.).

Upon estimation of (7) two sets of elasticities can be computed, e_{ij}^{L} for losses (i.e. when $I_i = 1$) and e_{ij}^{G} for gains (i.e. $I_i = 0$), respectively:

$$
e_{ij}^{L} = \frac{[-w_j + \sum_{j=1}^{N} \gamma_{ij} \log p_j + \sum_{j=1}^{N} \delta_{ij} (\log p_j - \log r_j)](\beta_{i1} + 2\beta_{i2} y^{L}) + \gamma_{ij} + \delta_{ij}}{w_i} - \Delta_{ij} \tag{9}
$$

where

$$
\begin{aligned}
y^{L} = & \log x - \sum_{j=1}^{N} w_j \log p_j + 0.5 \sum_{j=1}^{N} \sum_{k=1}^{N} \gamma_{jk} \log p_j \log p_k + \\
& 0.5 \sum_{j=1}^{N} \sum_{k=1}^{N} \delta_{jk} (\log p_j - \log r_j)(\log p_k - \log r_k)
\end{aligned} \tag{10}
$$

$$e_{ij}^G = \frac{[-w_j + \sum_{j=1}^N \gamma_{ij} \log p_j + \sum_{j=1}^N \omega_{ij}(\log r_j - \log p_j)](\beta_{i1} + 2\beta_{i2} y^G) + \gamma_{ij} + \omega_{ij}}{w_i} - \Delta_{ij} \quad (11)$$

where

$$\begin{aligned} y^G = \log x - \sum_{j=1}^N w_j \log p_j + 0.5 \sum_{j=1}^N \sum_{k=1}^N \gamma_{jk} \log p_j \log p_k + \\ 0.5 \sum_{j=1}^N \sum_{k=1}^N \omega_{jk} (\log r_j - \log p_j)(\log r_k - \log p_k) \end{aligned} \quad (12)$$

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

3. Empirical Application

3.1. Raw Data

We use data on household expenditures between January 2012 and December 2015 from the Great Britain (GB) Kantar Fast Moving Consumer Good (FMCG) panel[8]. The GB Kantar FMCG panel is a representative consumer panel of food and beverages purchased by households in GB (i.e. England, Wales and Scotland) and brought into their home. Purchases are made in a variety of outlets, such as major retailers, supermarkets, butchers, greengrocers, and corner shops. Home scan data are collected from each participant household via supplied hand-held scanners which households use to scan barcodes of purchased products.

Data are collected from a sample of more than 30,000 GB households each year, stratified according to household size, number of children, social class, geographical region and age group. Our raw data-set consists of individual transactions, including information on the day of the purchase, outlet, amount spent, and volume purchased. The unit value paid by the household can be obtained by dividing expenditure by quantity. At the at the universal product code (UPC) level (e.g. a can of cherry Cola is a distinct good from a bottle of cherry Cola of the same brand), this unit value corresponds to the shelf price. In addition, socio-demographic data describes household size and composition, age, ethnicity and highest qualification of the

[8]See www.kantarworldpanel.com/en

main shopper. It also includes information on the geographical location (postcode district), income group, occupational socio-economic class and tenure of the household. Furthermore, Kantar provides nutritional information for products through direct measurement in outlets, or using product images supplied by Brandbank, a third-party supplier.
The basic observation is the individual transaction, which means that products are disaggregated at the UPC level.

In our empirical application, we consider drink purchases only, with different product aggregation levels considered in each study, UPC and aggregate drink category, respectively. We use data for the years 2012-2014 as the estimation sample, and the year 2015 for the evaluation of the out-of-sample model performance.

3.2. Empirical definitions 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 simplest definition implies that consumers have in mind the price from their latest purchase, which they compare with the shelf price. Hence, the reference prices for a single good i at time t is:

$$r_{it} = p_{is} \quad \text{with} \quad s \leq t-1 \tag{13}$$

When a single good is considered, the obvious choice for the reference period s is the most recent time period when that specific good was purchased. However, this might not be the most accurate scenario. In their shopping trips, consumers may decide not to purchase a good while knowing its price, and buy a substitute. Therefore, a more realistic choice refers to the last shopping trip where at least one good from the target basket was purchased. Under this definition, IRPs can be treated as exogenous. By definition, consumer form their references before their choice, and empirically they depend on lagged prices and are predetermined.

An extensive discussion of alternative empirical specification for reference prices is provided in Briesch et al. (1997). For example, IRPs may also be assumed to include a combination rather than just one previous price, as in adaptive theories, or one may assume that consumer exploit current stimuli in their shopping environment rather than from their memory, as captured by ERPs[9].

3.3. Discrete Choice Model

Data and Empirical Model

The application ot the DCM considers the choice of a cola bottle sized one liter or more, as colas are the most consumed soft drink in the UK and in most countries. We consider products at the highest disaggregation level, as identified by the UPC code. We restrict purchases to those made at a single retailer to exclude price and promotion variations between different supermarket chains. We select the retailer with the highest cola sales volume over the estimation sample. The choice set includes those cola products with the highest total purchases for the selected retailer (at least 10,000 liters over three years), after excluding multi-pack products and flavored products (e.g. cherry cola). The final choice set includes seven products, of which five are branded colas and two are private labeled colas. All the colas in the final choice set are in two-liters bottles. The seven products account for 78% of total cola sales at the selected retailer. In order to define a reference price for each household and product, we only retain households that purchased any cola from the choice set in at least two subsequent weeks, which should mitigate memory biases. Hence, the reference price for each product in week t is the price at $t-1$.

The final sample for estimation includes $n = 1,877$ distinct households, of which 61% ($n = 1,148$) appear in a single year, 26% ($n = 488$) appear in two years, and 13% ($n = 241$) appear in all three years of the estimation sample. The sample used for validation includes $n = 806$ households. Table 1 presents descriptive statistics on the households belonging to the DCM sample.

In order to retrieve prices for non-purchased products, we follow the approach proposed by Dubois et al. (2017) and Griffith et al. (2018) using the same data source. The industry wide agreement on national pricing policy between food retailers and the UK Competition Commission (Nakamura et al., 2015) prescribes that retailers apply the same prices in all of

[9]Recent research based on experimental data has also explored the role played by uncertainty in reference prices (Caputo et al., 2020). Our proposed specifications of the DCM and CDS with reference prices is flexible to different definitions of reference prices, but for the goal of this study we focus on the standard formulations

Table 1. Descriptive statistics: Sample for Discrete Choice Model estimations.

	2012-14		2015	
	Mean	St. Dev.	Mean	St. Dev.
Household size	3.28	1.34	3.29	1.30
Age of main shopper	43.88	11.48	45.33	11.69
Number of children	0.92	1.09	0.84	1.04
Number of children if have children	1.75	0.89	1.73	0.83

	Percent of Households	Percent of Households
Households with children	52.7	48.6
Income		
£0 - £9,999 pa	6.8	6.3
£10,000 - £19,999 pa	22.6	21.7
£20,000 - £29,999 pa	23.1	22.8
£30,000 - £39,999 pa	19.4	19.6
£40,000 - £49,999 pa	13.5	13.3
£50,000 - £59,999 pa	6.8	8.1
£60,000 - £69,999 pa	4.1	4.8
£70,000 +	3.7	3.4
Occupational Socio-economic Grade		
Class AB (highest)	16.7	16.1
Class C1	36.3	35.7
Class C2	22.0	20.2
Class D	16.6	19.9
Class E	8.5	8.1
Education of RP (highest qualification)		
Degree or higher	21.8	22.2
Higher education	16.0	17.9
A Level	14.7	14.9
GCSE	25.7	28.4
Other	8.8	7.0
None	7.2	6.8
Unknown	5.7	2.9
Tenure Type		
Owned outright	13.3	17.0
Mortgaged	49.6	48.4
Rented	33.9	31.5
Other	1.5	1.0
Unknown	1.8	2.1
Number of households	1,877	806
Number of observations	11,501	3,630

their UK branches for the same type of shops on the same day (e.g. products have the same price in all Tesco Metro branches which may differ from the prices in Tesco Express branches). As our data refer to a single retailer, given the agreement, the variability in observed prices during the same week across households is small, as it only depends on the fact that our time reference unit is the week, and different household may have shopped on different days of the same week. Thus, we classify households into 11 GB regions, and we define weekly regional prices for each product in the choice set as the modal unit value paid within each region and week. By doing so, we have information about prices and reference prices for all alternatives in the choice set, including those products not purchased in a specific shopping trip.

Table 2 displays the main characteristics of products in the choice set, including their average price.

Table 2. Choice set products and attributes.

	Brand	Sugar	Av. Price £(std dev)	N	Market Share
Product1	Branded	0.0	1.06 (0.20)	3740	32.50
Product2	Branded	10.6	1.27 (0.35)	1733	15.06
Product3	Branded	0.0	1.28 (0.36)	981	8.53
Product4	Branded	11.0	1.03 (0.14)	2089	18.16
Product5	Branded	0.0	1.04 (0.16)	1345	11.69
Product6	Private label	0.0	0.53 (0.07)	760	6.61
Product7	Private label	10.7	0.54 (0.07)	858	7.46

Notes: Sugar is the sugar content in g/100ml; N is the number of purchases in the dataset; Prices are in GB pounds (£) per bottle (2 lt): prices for non-purchased products are defined as the average of modal unit values by region and week within the same retailer.

Losses and gains are calculated as the absolute difference between price of the product and the reference price, and they only occur when the distance between the actual price and the reference price exceeds a threshold of £0.05. Trimming observations below this cutoff reduces losses and gains occurrence and increases their average magnitude, ensuring a fair discrimination. Table 3 displays descriptive statistics of losses and gains for each product in the choice set, in the three years estimation period.

The attributes included in the empirical model are price, gain, loss and sugar content in grams/100ml. The DCM also includes socio-demographic variables, namely income level (in £per year), household size, number of children living in the house, occupational socio-economic (a dummy for AB class), type of tenure (dummies for own and mortgaged relative to other types), highest level of education (dummies for degree or higher and higher education relative to other education levels). To address potential price endogeneity, we implement the control function approach by using prices for the same product and week in other regions as the

Table 3. Proportion of losses and gains, and average distance from the reference price.

	Proportion of losses	Average loss	Proportion of gains	Average gain
Product1	9.9%	0.62 (0.23)	10.6%	0.57 (0.20)
Product2	15.1%	0.50 (0.29)	17.0%	0.47 (0.26)
Product3	15.0%	0.50 (0.29)	17.1%	0.47 (0.26)
Product4	9.0%	0.57 (0.23)	9.1%	0.58 (0.18)
Product5	9.2%	0.60 (0.21)	9.9%	0.54 (0.19)
Product6	1.9%	0.08 (0.04)	2.6%	0.10 (0.04)
Product7	1.3%	0.10 (0.06)	2.0%	0.11 (0.06)

Notes: Average losses (gains) are the average distance between the actual price and the reference price conditional on losses (gains). Standard deviations in parentheses.

instruments.

Results

Table 4 reports the key results in terms of choice response to price changes. Changes in market shares are shown in relation to a 10% price increase or decrease, as estimated by the standard DCM and a DCM augmented with reference price effects. The model without reference prices predicts a relatively larger response to price decreases, compared to equal sized price increases, which would contradict loss aversion. Instead, when reference prices are accounted for, our estimates reflect loss aversion and predict a greater response to a price increase, with only one exception for Product 5. Interestingly, we see a higher response for change in price of Product1, which is the product with the highest market share, and therefore the most preferred product by consumers. Price changes for this product affect purchase probability to a greater extent, compared to other products[10].

Table 4 includes also model diagnostics that tend to favor the DCM with reference prices, which show a higher log-likelihood, lower BIC and AIC, and better in-sample (2012-14) and out-of-sample (2015) prediction performances. As the two models are nested, the significant likelihood ratio test also supports the adoption of the extended specification.

Robustness checks

We explore the sensitivity of our results to two variations in the definition of the reference prices. Table 5 compares results from the baseline model (DCM with reference price effect above a 5p threshold) to two alternative sets of estimates: (i) with a larger threshold in the IRP definition , i.e. losses and gains are only considered above a more restrictive 10p threshold; (ii) using an

[10]Cross-effects, i.e. the impact on market share in response to gains and losses associated with price changes in other goods, are shown in Appendix A4.

Table 4. Simulated changes in market shares following a 10% price change in each product.

	Without Reference Prices			With Reference Prices		
	M. S. (%)	↑ 10%	↓ 10%	M. S.	↑ 10%	↓ 10%
Product1	26.40	-4.39 (0.024)	4.88 (0.029)	27.43	-5.75 (0.019)	3.92 (0.023)
Product2	13.20	-1.18 (0.012)	1.73 (0.015)	12.90	-1.74 (0.011)	1.20 (0.013)
Product3	10.43	-0.61 (0.014)	1.57 (0.019)	10.04	-1.17 (0.013)	0.85 (0.015)
Product4	21.27	-2.33 (0.017)	2.60 (0.020)	19.67	-2.81 (0.015)	2.05 (0.019)
Product5	11.08	-2.34 (0.019)	4.90 (0.025)	11.36	-3.12 (0.016)	3.90 (0.021)
Product6	10.68	-1.87 (0.014)	1.90 (0.013)	11.61	-2.16 (0.012)	1.80 (0.011)
Product7	6.93	-1.26 (0.010)	1.30 (0.010)	7.00	-1.36 (0.010)	1.15 (0.009)
Likelihood			-12243.3			-12164.1
LR test						158.3 ($p<$ 0.01)
AIC			24588.5			24434.3
BIC			25062.6			24927.0
In sample RMSE			0.032			0.029
Out of sample RMSE			0.044			0.041

Notes: M.S.= market share (average choice probabilities as simulated by the models with original prices); bootstrap standard errors in parentheses.

external reference price based on the mean value of current prices of all the available alternatives (Mazumdar et al., 2005). The models consistently display loss aversion and response asymmetry. Changing the threshold leads to very small changes in choice responses, and the direction of asymmetries is confirmed. The difference when an ERP is adopted is larger, and in two cases (Product2 and Product3) there is a switch in the direction of the asymmetries. As seen in other studies and as expected, while the difference in estimates between IRPs and ERPs are relatively large (Briesch et al., 1997), they still show good evidence of asymmetric price response.

Table 5. Robustness checks: Market share response under alternative reference price specifications.

	Original Model (with RP)		10p threshold		Mean Current RP	
	↑ 10%	↓ 10%	↑ 10%	↓ 10%	↑ 10%	↓ 10%
Product1	-5.75 (0.019)	3.92 (0.023)	-5.87 (0.022)	3.65 (0.020)	-2.84 (0.043)	1.79 (0.051)
Product2	-1.74 (0.011)	1.20 (0.013)	-1.70 (0.015)	1.02 (0.012)	-1.40 (0.015)	1.76 (0.020)
Product3	-1.17 (0.013)	0.85 (0.015)	-1.30 (0.019)	0.77 (0.022)	-1.02 (0.020)	1.88 (0.029)
Product4	-2.81 (0.015)	2.05 (0.019)	-2.70 (0.012)	1.81 (0.009)	-1.19 (0.018)	1.04 (0.021)
Product5	-3.12 (0.016)	3.90 (0.021)	-3.23 (0.017)	3.69 (0.019)	-0.65 (0.046)	2.42 (0.039)
Product6	-2.16 (0.012)	1.80 (0.011)	-2.06 (0.011)	1.69 (0.008)	-1.04 (0.004)	0.95 (0.004)
Product7	-1.36 (0.010)	1.15 (0.009)	-1.30 (0.004)	1.07 (0.004)	-0.72 (0.003)	0.66 (0.003)
RMSE (in)	0.029		0.027		0.022	
RMSE (out)	0.041		0.038		0.031	

Notes: Standard errors in parentheses.

Simulation

We stimulate how purchase choice respond to two different fiscal policies, a tax on sugar sweetened colas and a subsidy for colas without sugar. The simulated tax mimics the UK sugar levy scheme, i.e. a 2 liter bottle of cola with more than 8g sugar/100ml (product 2, 4 and 7 in the choice set) is taxed 48p, as the levy charges 24p per liter. For the subsidy policy, we simulate the effects of a 25p discount for sugar-free colas (products 1, 3, 5 and 6 of the choice set). Table 6 compares the simulations obtained from the DCM without and with reference prices, respectively.

Overall, for the 48p tax the reallocation of choices towards sugar free products is relatively small and only slightly larger for the model accounting for gains and losses (1.38& vs. 1.09%). The difference in simulations is more evident for the subsidy case. Ignoring gains and losses lead to a relatively small effect (a 0.58% increase in the market share for sugar free products), but the augmented model captures a four-fold larger variation (2.31%).

Interestingly, the simulated effects of the fiscal measures affecting multiple products are lower than the market share responses observed when only one price changes (table 4), despite the tax and the subsidy being higher than 10%. This is because the simulations reflect consumer evaluation of price changes, losses and gains associated with all products in the choice set, including on what normally might be considered as a substitute (e.g. sugary colas taxed at the same time). In other words, households partly substitute one taxed drink with another cheaper taxed drink, rather than switch to sugar-free drinks. This also means that loss aversion as captured by changes in a single product price does not necessarily imply that taxation on multiple products has larger effects compared to subsidies on several products.

Table 6. Simulated changes in market shares (%) in response to sugar taxes (48p on sugared products) and subsidies (25p on sugar free products).

		Without Reference Price			With Reference Price		
		M. S.	+ 48p	- 25p	M. S.	+ 48p	- 25p
Product1	Sugar free	26.40	0.44 (0.025)	0.23 (0.014)	27.43	0.60 (0.025)	1.29 (0.011)
Product2	Taxed	13.20	-0.15 (0.023)	-0.08 (0.013)	12.90	-0.30 (0.023)	-0.05 (0.011)
Product3	Sugar free	10.43	0.00 (0.022)	0.00 (0.012)	10.04	0.05 (0.019)	-0.23 (0.009)
Product4	Taxed	21.27	-0.27 (0.030)	-0.14 (0.018)	19.67	-0.35 (0.029)	-1.89 (0.015)
Product5	Sugar free	11.08	0.17 (0.025)	0.09 (0.013)	11.36	0.23 (0.022)	0.28 (0.010)
Product6	Sugar free	10.68	0.48 (0.036)	0.26 (0.020)	11.61	0.51 (0.038)	0.97 (0.018)
Product7	Taxed	6.93	-0.66 (0.036)	-0.35 (0.022)	7.00	-0.74 (0.031)	-0.37 (0.016)
Total taxed		41.41	-1.09 (0.053)	-0.58 (0.031)	39.57	-1.38 (0.048)	-2.31 (0.025)
Total sugar free		58.59	1.09 (0.055)	0.58 (0.030)	60.43	1.38 (0.054)	2.31 (0.025)

Notes: M.S.= market share (average choice probabilities as simulated by the models with original prices, %); bootstrap standard errors in parentheses.

3.4. Continuous Demand System

Data and Empirical Model

For market-level policy simulations, the application of demand systems to aggregate product categories may be preferred. We demonstrate the extension of CDS to account for reference price effects by estimating a six-good EASI model conditional on total beverage expenditure for the considered drink categories. We adopt an aggregation strategy which is consistent with the UK 2018 sugar levy.

Thus, we aggregate UPC codes into the following six categories: (i) sugar free soft drinks; (ii) sugar-sweetened beverages with sugar lower than 5g/100 ml; (iii) SSBs with sugar between 5g and 8g; (iv) SSBs with sugar exceeding 8g/100ml; (v) still and carbonated water; and (vi) beer and cider.

We reshape the transaction-level raw data into a pooled data-set where the basic observation is the household/week. Thus, for each of the aforementioned drink categories we sum the purchased volumes and amount spent over each household and week. The final sample for our CDS analysis includes all households with positive total expenditure on the selected goods for at least two weeks over six consecutive weeks in the three-year period. This means that we consider a purchase only if the same household had another recorded purchase from the same set of categories in one of the previous 5 weeks, to avoid introducing memory biases associated with infrequent purchases. This enables us to calculate household-specific reference prices, based on their previous drink purchase. For 68% of observations the reference price was based on a shopping trip in the previous week; for 19% of observations the reference price referred to a shopping trip two weeks before the current purchase; the remaining 7%, 4% and 2% of observations had reference prices based on shopping trips 3, 4 and 5 weeks earlier, respectively. As for the DCM, we use data in the period 2012-2014 for estimation purposes and observations in the year 2015 are used to assess out-of-sample performance. After aggregation and exclusion of observations with missing values in demographic variables, the final data-set contains nearly 1.8 million observations for $31,214$ households, and on average each household reports purchases for at least one of the beverage categories over 87 weeks; 23% ($n = 7,169$) of the sampled households have recorded purchases in a single year, 12% ($n = 3,841$) appear in two years, and 65% ($n = 20,204$) appear over all three years. The sample used for validation includes $n = 25,021$ households and $582,708$ observations.

Table 7 displays the key socio-demographic characteristics of the CDS sample. These socio-demographic statistics are in line with the official statistics for Great Britain[11].

Table 7. Descriptive statistics: Sample for Continuous Demand System estimations.

	2012-14		2015	
	Mean	St. Dev.	Mean	St. Dev.
Household size	2.74	1.33	2.73	1.32
Age of main shopper	48.16	15.04	49.66	14.67
Number of children	0.68	0.99	0.64	0.97
Number of children if have children	1.72	0.85	1.74	0.82
	Percent of Households		Percent of Households	
Households with children	40.3		36.7	
Income				
£0 - £9,999 pa	9.6		7.9	
£10,000 - £19,999 pa	24.8		23.2	
£20,000 - £29,999 pa	21.9		22.0	
£30,000 - £39,999 pa	16.6		16.8	
£40,000 - £49,999 pa	11.5		12.0	
£50,000 - £59,999 pa	7.0		7.6	
£60,000 - £69,999 pa	3.8		4.3	
£70,000 +	4.9		6.1	
Occupational Socio-economic Grade				
Class AB (highest)	21.4		21.7	
Class C1	36.8		38.9	
Class C2	18.7		17.7	
Class D	14.0		13.6	
Class E	9.1		8.2	
Education of RP (highest qualification)				
Degree or higher	29.1		30.8	
Higher education	16.0		16.3	
A Level	15.7		14.6	
GCSE	22.9		22.5	
Other	8.5		8.2	
None	7.9		7.8	
Tenure Type				
Owned outright	25.0		27.5	
Mortgaged	42.7		42.1	
Rented	31.1		29.0	
Other	1.3		1.5	
Number of households	31,214		25,021	
Number of observations	1,759,558		582,708	

Unit values for each food group are calculated as the ratio of the amount spent over the quantity purchased. In order to control for the quality choice component in unit values, we follow the standard assumption that households living in the same area face the same prices during the same week (Deaton, 1988). Since we follow a system-wise approach, this approach

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

also allows to retrieve information on the price of non-purchased substitute goods. The households in our data-set are classified into 110 postcode areas[12], and we exploit this geographical disaggregation to obtain an estimate of local prices for all drink categories by averaging the unit values paid within each postcode and week:

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

where x_{iht} is the amount spent in period t by a household h to purchase all products included in the drink category 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. Table 8 reports average quantities, expenditure and prices for the estimation sample. About 47% of the selected purchases include a soft drink with more than 8g/100ml of sugar. Purchase frequencies for low-sugar (less than 5g/100ml) soft drinks are equally high (47.3%). The proportion of diet (sugar free) soft drink purchases is lower (36%). Beer and cider are purchased more frequently than water (23% and 13% of purchases, respectively). In their average shopping trip, households buy about 7.1 liters of drinks. Considering purchases only (i.e. excluding all weeks with no purchases), the average weekly purchase of mineral water is almost exactly 6 liters, but weekly purchases of beers and ciders (5.3 litres) and diet soft drinks (4.8 litres) are also high.

As prices and reference prices refer to aggregate categories, their variation across postcodes and weeks reflects both changes in actual prices and potential differences in the category composition. Thus, we adopt a more conservative approach and define non-zero gain and losses only when the gap between the price and the reference price exceeds 10p. Table 9 shows the proportion of household-week observations where a loss or a gain is identified for each drink category, and the average distance from the reference price. Losses and gains follow a similar distribution across the drink categories, and their size is also almost identical, which probably reflects the fact that the sizes of price increases and price cuts (promotions) for individual products are relatively standard.

All estimated models include the same socio-demographic variables as the DCM (household

[12]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

Table 8. Purchase data (estimation sample).

	All observations			Purchases	Purchases only	
	Exp	Vol	Price	%	Exp	Vol
Sugar-free soft drinks	1.00	1.71	0.60	35.8	2.79	4.78
	(2.21)	(3.50)	(0.08)		(2.95)	(4.42)
SSBs ($< 5g$ sugar/100 ml)	1.01	1.51	0.69	47.3	2.13	3.19
	(1.64)	(2.56)	(0.09)		(1.82)	(2.92)
SSBs ($5 - 8g$ sugar/100 ml)	0.22	0.21	1.09	9.9	2.23	2.12
	(0.91)	(0.85)	(0.41)		(1.98)	(1.78)
SSBs ($> 8g$ sugar/100 ml)	1.46	1.67	0.88	47.0	3.11	3.55
	(2.55)	(2.99)	(0.09)		(2.96)	(3.52)
Water	0.22	0.78	0.29	12.9	1.71	6.01
	(0.83)	(2.90)	(0.07)		(1.65)	(5.79)
Beer and cider	2.27	1.22	1.92	22.9	9.93	5.32
	(6.26)	(3.64)	(0.22)		(9.74)	(6.00)
Total	6.18	7.10		100.0		
	(7.39)	(7.14)				
Households	31,214					
Observations	1,759,558					

Notes: Standard deviations in parentheses. Drink quantities are expressed in liters per week. Expenditures are in GB pounds (£) per week. Prices and unit values are in £/Liter. Prices are the average of unit values by postcode area and week. Purchases refer to household weeks with non-zero expenditure in a specific product category.

size, income, number of children in the household, social class, type of tenure, highest education level). Potential endogeneity of prices is addressed by instrumenting them through prices for the same products in the same week and in other regions, just like the control function approach of the DCM model[13].

Results

Table 10 shows the own-price elasticities for the standard EASI model, together with those for the augmented model in (7), together with some model diagnostics. Like for the DCM, the model with reference prices has a slightly better fit in terms of likelihood, AIC and BIC, and the likelihood rato test is significantly in favor of the extended model. However, the two models display a very similar performance in terms of in-sample and out-of-sample predictions. What is more interesting is the clear gap between loss and gain own-price elasticities, which brings clear evidence towards asymmetric price response and loss aversion for all drink categories.

[13]Instrumenting prices bring very minor changes to the estimated elasticities, and a minor loss of efficiency, but also a slightly superior out-of-sample forecast performance. Hence, we report here only the results for models with instrumented prices, but estimates for models without instrumenting are available as on-line Supplemental Material

Table 9. Proportion of Losses and Gains, and Average Distance from Reference Price.

	Proportion of losses	Average loss	Proportion of gains	Average gain
Sugar-free soft drinks	6.9%	0.14 (0.04)	6.6%	0.14 (0.04)
SSBs ($< 5g$ sugar/100 ml)	9.3%	0.15 (0.05)	9.5%	0.15 (0.05)
SSBs ($5 - 8g$ sugar/100 ml)	36.2%	0.33 (0.36)	34.9%	0.33 (0.37)
SSBs ($> 8g$ sugar/100 ml)	9.2%	0.15 (0.05)	8.9%	0.15 (0.05)
Water	6.0%	0.15 (0.08)	5.9%	0.15 (0.08)
Beer and cider	27.2%	0.23 (0.13)	26.9%	0.23 (0.14)

Notes: Average losses (gains) are the average distance between the actual price and the reference price conditional on losses (gains). Standard deviations in parentheses.

As one would expect, elasticities for the baseline model lie between the gain and loss value (in absolute terms), but lean towards the latter, again consistently with loss aversion which implies a stronger response to increasing prices. As the same unbalance is observed for cross-price elasticities [14], ignoring the asymmetry leads to a higher biases when predicting response to a price decrease (subsidy) than a price increase (tax).

Table 10. Own Price Elasticities.

	Without Reference Price	With Reference Price	
	Elasticity	Loss Elas.	Gain Elas.
Sugar-free soft drinks	-0.81 (0.02)	-1.04 (0.03)	0.62 (0.02)
SSBs ($< 5g$ sugar/100 ml)	-0.85 (0.01)	-0.97 (0.02)	0.66 (0.02)
SSBs ($5 - 8g$ sugar/100 ml)	-0.74 (0.01)	-0.86 (0.02)	0.56 (0.01)
SSBs ($> 8g$ sugar/100 ml)	-1.13 (0.01)	-1.23 (0.01)	0.68 (0.03)
Water	-1.12 (0.02)	-1.36 (0.04)	0.67 (0.04)
Beer and cider	-1.41 (0.02)	-1.87 (0.03)	0.83 (0.04)
Likelihood	-461966.8		-460822.6
LR test			2288.4***
AIC	923951.6		921663.2
BIC	924063.0		921774.5
In sample RMSE	0.31029		0.31025
Out of sample RMSE	0.31691		0.31685

Notes: Standard error in parentheses were obtained via the delta method on bootstrapped coefficient estimates. Loss elasticities are the percent changes in purchased quantities in response to a 1% increase in the price. Gain elasticities are the percent changes in purchased quantities in response to a 1% price decrease.

Robustness checks

We explore the robustness of the estimated elasticities by comparing our baseline estimates to different specifications. Table 11 shows the estimated loss and gain elasticities for the following models: (i) with a lower threshold in the IRP definition, i.e. losses and gains are considered

[14] The full set of elasticities is available in Appendix A4.

above a less restrictive 5p threshold (the same as the DCM); (ii) an EASI model where the reference price is based on an extrapolative expectation model (Nerlove, 1958; Kalwani et al., 1990; Putler, 1992) considering several past prices as described below; (iii) an Almost Ideal Demand System with reference prices as described by equation (A.8) in Appendix A3..

We specify the reference price from the extrapolative expectation model as a geometrically weighted moving average of a set of past prices of the same good, where the weights are normalized to sum to one:

$$r_{it} = \left(\sum_{h=1}^{L} \rho_i^h \right)^{-1} \sum_{s=1}^{L} \rho_i^s p_{i,t-s} \tag{14}$$

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. For our robustness check, we assume five lags.

Changing the threshold for defining loss and gains or adopting the extrapolative expectation model for reference prices bring very minor changes in the elasticity estimates relative to the baseline model, and the three models have very similar in-sample and out-of-sample predictive performance. Estimates from the AIDS model are also consistent and in line with a strong loss aversion.

Table 11. Robustness checks: Own price elasticities under alternative reference price and demand system specifications.

	5p threshold		Adapt. Expect. RP		AIDS model	
	Loss	Gain	Loss	Gain	Loss	Gain
Sugar-free soft drinks	-1.04 (0.02)	0.59 (0.02)	-1.08 (0.03)	0.57 (0.03)	-1.06 (0.02)	0.64 (0.02)
SSBs $< 5g$	-0.95 (0.01)	0.64 (0.02)	-0.95 (0.02)	0.55 (0.02)	-1.09 (0.02)	0.73 (0.02)
SSBs $5 - 8g$	-0.94 (0.01)	0.41 (0.01)	-0.96 (0.01)	0.39 (0.01)	-0.93 (0.02)	0.40 (0.02)
SSBs $> 8g$	-1.16 (0.03)	0.69 (0.02)	-1.17 (0.03)	0.56 (0.02)	-1.31 (0.02)	0.85 (0.02)
Water	-1.31 (0.01)	0.68 (0.01)	-1.33 (0.02)	0.55 (0.03)	-1.27 (0.02)	0.60 (0.02)
Beer and cider	-1.87 (0.05)	0.85 (0.03)	-1.90 (0.04)	0.58 (0.06)	-1.35 (0.02)	0.66 (0.02)
In sample RMSE		0.312		0.310		0.305
Out of sample RMSE		0.318		0.317		0.310

Notes: Standard error in parentheses were obtained via the delta method on bootstrapped coefficient estimates. Loss elasticities are the percent changes in purchased quantities in response to a 1% increase in the price. Gain elasticities are the percent changes in purchased quantities in response to a 1% price decrease

The EASI specification accounts for the effects of observed (linked to demographics) and unobserved taste heterogeneity, but following Lusk (2017) we exploit the large sample size of our data-set to explore differences in preferences across clusters of consumers and estimate separate demand systems for each subgroup. Table 12 reports the own price elasticities for subgroups of the population, depending on their income and the level of consumption of drinks. We distinguish between lower income households (less than £20,000 per year) and higher income households (more than 30,000 £per year), and between heavy shopping households (an average purchase above 2.5 liters per capita per week with non-zero purchase) and light shopping households (below 2.5 liters per capita per week). Although the differences are not large, they are in line with the expectation. Lower income household are in general more elastic to price changes, in terms of both loss and gain elasticities, whereas loss aversion intended as the distance between absolute loss and gain elasticities is similar across the two groups. When comparing households with different level of average weekly purchases, we find that heavier purchasers are in general more elastic to price increases, whereas the difference in gain elasticities relative to lower purchasers is small, which suggests that a higher purchase level is associated with a stronger loss aversion.

Table 12. EASI demand system own-price Elasticities for population subgroups.

	Lower income		Higher income		Light shoppers		Heavy shoppers	
	Loss	Gain	Loss	Gain	Loss	Gain	Loss	Gain
Sugar-free soft drinks	-1.09	0.62	-1.00	0.58	-1.02	0.64	-1.02	0.49
	(0.03)	(0.04)	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)
SSBs $< 5g$	-0.95	0.73	-0.92	0.52	-0.89	0.56	-1.02	0.72
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)
SSBs $5-8g$	-1.00	0.51	-0.88	0.33	-0.88	0.41	-1.01	0.47
	(0.03)	(0.04)	(0.02)	(0.02)	(0.02)	(0.02)	(0.05)	(0.03)
SSBs $> 8g$	-1.16	0.74	-1.13	0.61	-1.06	0.65	-1.31	0.71
	(0.03)	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.04)
Water	-1.32	0.66	-1.33	0.58	-1.09	0.53	-1.45	0.68
	(0.05)	(0.04)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)
Beer and cider	-1.91	0.95	-1.77	0.80	-1.62	0.86	-2.18	0.77
	(0.10)	(0.08)	(0.05)	(0.07)	(0.06)	(0.07)	(0.06)	(0.06)
In sample RMSE		0.313		0.309		0.311		0.311
Out of sample RMSE		0.320		0.315		0.319		0.316

Notes: Standard error in parentheses were obtained via the delta method on bootstrapped coefficient estimates. Loss elasticities are the percent changes in purchased quantities in response to a 1% increase in the price. Gain elasticities are the percent changes in purchased quantities in response to a 1% price decrease

Simulation

Table 13 shows simulations based on the EASI demand system without and with reference prices. As for the DCM we compare the two models under a taxation scenario and a subsidy scenario. The former is based on the 2018 UK sugar levy, i.e. soft drinks are not taxed if they contain less than 5 grams of sugar per 100ml, those with a sugar content between 5g and 8g per 100ml are taxed £0.18 per liter, and those exceeding 8g are taxed £0.24 per liter. The subsidy scenario simulates a £0.15 per liter subsidy on sugar free soft drinks and mineral water.

Under the tax scenario, simulations from the two models are quite similar, whereas larger differences emerge when considering subsidies, especially for mineral water that is predicted to increase substantially (+1.5 litres per week) in the model without reference prices, whereas it does not respond significantly to the subsidy when reference prices are considered. This result is consistent with the smaller discrepancy between the loss elasticities and elasticities estimates without considering reference prices as shown in Table 10. However, ignoring reference prices (including cross-effects) and loss aversion leads to biases when simulating the response to a price decrease. The system with reference prices also more realistic in terms of simulating total drink purchases. Under the subsidy scenario, we only observe a minor increase in total purchases (+0.33 liters per household per week), whereas the model without reference prices predicts an unlikely increase in purchased quantities by 1.71 liters per household per week.

Table 13. Difference in quantity consumed in response to the simulated fiscal intervention.

	Without Reference Price			With Reference Price		
	Quantity	Tax	Subsidy	Quantity	Tax	Subsidy
Sugar free soft drinks	1.76	0.07 (0.013)	0.12 (0.020)	1.75	0.08 (0.017)	0.22 (0.027)
SSBs sugar $< 5g$	1.47	0.18 (0.011)	-0.07 (0.013)	1.46	0.22 (0.013)	-0.04 (0.022)
SSBs sugar $5 - 8g$	0.21	-0.02 (0.003)	0.01 (0.004)	0.22	-0.03 (0.003)	0.02 (0.005)
SSBs sugar $> 8g$	1.66	-0.43 (0.008)	0.01 (0.011)	1.64	-0.46 (0.008)	-0.06 (0.017)
Water	0.86	-0.16 (0.016)	1.52 (0.077)	0.85	-0.14 (0.019)	-0.03 (0.123)
Beer and cider	1.20	-0.03 (0.010)	0.14 (0.033)	1.22	-0.02 (0.012)	0.18 (0.053)
Taxed SSBs	1.87	-0.45 (0.009)	0.02 (0.011)	1.86	-0.49 (0.009)	-0.04 (0.017)
Non-taxed drinks (exc. Beer)	4.10	0.09 (0.023)	1.57 (0.080)	4.06	0.16 (0.028)	0.15 (0.128)

Notes: Standard error in parentheses. Quantity = baseline quantity in liters/week. The tax and subsidy columns report estimated changes in purchased quantities consumed (in liters/week) under the tax and subsidy scenarios. The simulated tax follows the UK sugar tax scheme, i.e. 18p per liter for soft drinks with 5-8g sugar/100ml and 24p/litre for drinks with more than 8g sugar/100ml; the simulated subsidy envisages a 15p/liter discount for diet soft drinks and water

4. Summary and Conclusion

This study explores the effects of ignoring asymmetries in demand response to price increases and decreases at different level of product aggregation and using different empirical demand models. We extend the specifications of a RUM-based discrete choice model and of an EASI demand system to include reference price effects, both models allowing for observed and unobserved preference heterogeneity. We estimate the models by drawing appropriate purchase and price data from a large scan data set for Great Britain, with a focus on the demand for soft drinks.

Estimates confirm previous empirical evidence of substantial asymmetries when considering high product disaggregation and discrete consumer choices. We extend the evidence to the case of aggregate product categories and continuous demand systems, which allows to consider cross-reference price effects as for the DCM. Although the behavioral underpinnings of reference prices and transaction utility have been previously discussed for highly differentiated products (e.g. at the UPC level), our results suggest that they also hold for more aggregate product categories. In our case, this also follows from the finding that the products we consider are all subject to loss aversion, so that loss elasticities are systematically higher than gain elasticities even after aggregation.

For both models, our findings are relatively robust to different choices in reference price specifications. Consumers are loss averse and a larger demand response is observed when prices rise above the reference level (loss) compared to a corresponding decrease below the reference price (gain). This findings holds with aggregate products. We also find that loss and gain elasticities are larger for low-income households, and heavy purchasing households are more loss averse than their light purchasing counterpart.

When reference prices are ignored, the estimated demand response is closer to the loss case relative to gains. This is also consistent with loss aversion emerging from the data, given that our data-set contained a balanced proportion of losses and gains. Consequently, the bias from ignoring the reference prices is relatively small when simulating a price increase, but simulations can be misleading when considering a price cut or a subsidy. Our results are inevitably specific to the choice of the product set, and to the selected definitions for reference prices. The extension of previous empirical findings on reference price effects and loss aversion to demand systems and aggregate product categories, suggest that reference price effects matter for market level-simulations that are especially relevant for fiscal policy scenarios. To this purpose, it would be relevant to test whether our findings can be generalized to other product categories and alternative reference price specifications.

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A Appendix

A1. 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:

$$\frac{df_i(\mathbf{p}, \mathbf{r}, x)}{dp_j} = \frac{dh_i(\mathbf{p}, \mathbf{r}, u)}{dp_j} = \frac{\partial f_i}{\partial p_j} + \frac{\partial f_i}{\partial E}\frac{dE}{dp_j} \tag{A.1}$$

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[15] that:

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

Thus (A.1) 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

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

A2. EASI DEMAND SYSTEM WITH REFERENCE PRICES

The empirical EASI cost function in Pendakur (2009) can be augmented to include reference price effects:

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

$$
\begin{aligned}
\log C(\mathbf{p},\mathbf{r},\mathbf{z},u,\epsilon) =& u + 0.5\sum_{j=1}^{N}\sum_{k=1}^{N}\gamma_{jk}\log p_j \log p_k \\
&+ 0.5\sum_{j=1}^{N}\sum_{k=1}^{N}\delta_{jk} I_j(\log p_j - \log r_j)(\log p_k - \log r_k) \\
&+ 0.5\sum_{j=1}^{N}\sum_{k=1}^{N}\omega_{jk}(1-I_j)(\log r_j - \log p_j)(\log r_k - \log p_k) \\
&+ \sum_{j=1}^{N} m_j(u,\mathbf{z})\log p_j + \sum_{j=1}^{N}\epsilon_j \log p_j
\end{aligned} \tag{A.2}
$$

where the notation is the same as for equations (7) and $m_j(u)$ is a J-vector valued function in u with $\sum_{j=1}^{n} m_j(u) = 1$. Sheppard's lemma returns the following Hicksian budget share equation for each good $i = 1, ..., N$:

$$
\begin{aligned}
w_i = h(\mathbf{p},\mathbf{r},\mathbf{z},u,\epsilon) = m_i(u,\mathbf{z}) &+ \sum_{j=1}^{N}\gamma_{ij}\log p_j + \sum_{j=1}^{N}\delta_{ij} I_j(\log p_j - \log r_j) \\
&- \sum_{j=1}^{N}\omega_{ij}(1-I_j)(\log r_j - \log p_j) + \epsilon_i
\end{aligned} \tag{A.3}
$$

We can now proceed through the same steps as in Pendakur (2009), i.e. write explicitly $\sum_{j=1}^{N} w_j \log p_j$ and work on the cost function (A.2) to obtain implicit utility as a function of the observed total expenditure x and observable prices and reference prices, which leads to the following result:

$$
\begin{aligned}
y = u = \log x - \sum_{j=1}^{N} w_j \log p_j &+ 0.5\sum_{j=1}^{N}\sum_{k=1}^{N}\gamma_{jk}\log p_j \log p_k \\
&+ 0.5\sum_{j=1}^{N}\sum_{k=1}^{N}\delta_{jk} I_j(\log p_j - \log r_j)(\log p_k - \log r_k) \\
&- 0.5\sum_{j=1}^{N}\sum_{k=1}^{N}\omega_{jk}(1-I_j)(\log r_j - \log p_j)(\log r_k - \log p_k)
\end{aligned} \tag{A.4}
$$

which corresponds to equation (8). One may then adopt the following quadratic function for $m(u, \mathbf{z})$ to consider demographic shifters:

$$m_i(u, \mathbf{z}) = \beta_{i0} + \beta_{i1} y + \beta_{i2} y^2 + \zeta_i \mathbf{z} \tag{A.5}$$

The last passage requires substitution of (A.5) into (A.3) to generate the implicit Marshallian demand functions in (7). The theoretical requirements from consumer theory imply the adding-up condition across equations, i.e. $\sum_{i=1}^{N} \beta_{i0} = 1$, and $\sum_{i=1}^{N} \gamma_{ij} = \sum_{i=1}^{N} \delta_{ij} = \sum_{i=1}^{N} \omega_{ij} = \sum_{i=1}^{N} \beta_{i1} = \sum_{i=1}^{N} \beta_{i2} = \sum_{i=1}^{N} \zeta_{ik} = 0$ for all goods $j = 1, ..., N$ and ζ_{ik} is the coefficient of the generic demographic characteristic z_k within vector $\mathbf{z}$. The symmetry requirements apply to both the price coefficients, i.e. $\gamma_{ij} = \gamma_{ji}$, and the loss and gain coefficients $\delta_{ij} = \delta_{ji}$, $\omega_{ij} = \omega_{ji}$. Likewise, homogeneity of the implicit demand functions must be met by the price, loss and gain coefficients, i.e. $\sum_{j=1}^{N} \gamma_{ij} = \sum_{j=1}^{N} \delta_{ij} = \sum_{j=1}^{N} \omega_{ij} = 0$ for each equation i[16].

A3. Almost Ideal Demand System with reference prices

As for the costfunction of the EASI model, the flexible functional form of the cost function behind the Almost Ideal Demand System (AIDS) model (Deaton and Muellbauer, 1980) can be modified to allow for internal reference price effects and asymmetric elasticities. Reference prices are incorporated in the AIDS cost function to account for losses and gains as follows:

$$\log C(u, \mathbf{p}, \mathbf{r}) = (1 - u) \log a(\mathbf{p}, \mathbf{r}) + u \log b(\mathbf{p}, \mathbf{r}) \tag{A.6}$$

Where

$$\begin{aligned} \log a(\mathbf{p}, \mathbf{r}) = \alpha_0 &+ \sum_{k=1}^{n} \alpha_k \log p_k + 0.5 \sum_{i=1}^{n} \sum_{j=1}^{n} \gamma_{ij}^{*} \log p_i \log p_j \\ &+ 0.5 \sum_{i=1}^{n} \sum_{j=1}^{n} \delta_{ij} I_j (\log p_i - \log r_i)(\log p_j - \log r_j) \\ &- 0.5 \sum_{i=1}^{n} \sum_{j=1}^{n} \omega_{ij} (1 - I_j)(\log r_i - \log p_i)(\log r_j - \log p_j) \end{aligned} \tag{A.7}$$

[16]Putler (1992) argues that the omission of the loss and gain dimensions in empirical demand models might be the reason why many empirical tests of homogeneity fail.

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:

$$\begin{aligned} w_i = \alpha_i &+ \sum_{j=1}^{n} \gamma_{ij} \log p_j + \sum_{j=1}^{n} \delta_{ij} I_j (\log p_j - \log r_j) \\ &- \sum_{j=1}^{n} \omega_{ij} (1 - I_j)(\log p_j - \log r_j) + \beta_i \log\left(\frac{x}{P}\right) \end{aligned} \tag{A.8}$$

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:

$$\begin{aligned} \log P = \alpha_0 &+ \sum_{k=1}^{n} \alpha_k \log p_k + 0.5 \sum_{i=1}^{n} \sum_{j=1}^{n} \gamma_{ij}^{*} \log p_i \log p_j \\ &+ 0.5 \sum_{i=1}^{n} \sum_{j=1}^{n} \delta_{ij} I_j (\log p_i - \log r_i)(\log p_j - \log r_j) \\ &- 0.5 \sum_{i=1}^{n} \sum_{j=1}^{n} \omega_{ij} (1 - I_j)(\log r_i - \log p_i)(\log r_j - \log p_j) \end{aligned} \tag{A.9}$$

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 (A.9) where all prices are multiplied by κ. As for the EASI demand system, homogeneity only holds if $\sum_{j=1}^{n}\delta_{ij}I_j=0$ and $\sum_{j=1}^{n}\omega_{ij}(1-I_j)=0$ for each of the system equations. 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.

$$\begin{aligned}e_{ij}&=\frac{\partial\log q_i}{\partial\log p_j}=\frac{\partial w_i}{\partial\log p_j}\frac{1}{w_i}-\frac{\partial\log p_i}{\partial\log p_j}\\&=\frac{\gamma_{ij}}{w_i}+\frac{\delta_{ij}I_j}{w_i}-\frac{\omega_j(1-I_j)}{w_i}-\frac{\beta_i}{w_i}\eta_{ij}-\Delta_{ij}\end{aligned}\tag{A.10}$$

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.

A4. Elasiticty estimates

A4.4. Discrete choice model: Elasticities

Table A1. Own- and cross-price elasticities - 10% price increase, model without reference prices.

	Product1	Product2	Product3	Product4	Product5	Product6	Product7
Product1	-4.39 (0.024)	0.02 (0.003)	0.08 (0.010)	0.03 (0.004)	1.59 (0.022)	1.03 (0.013)	0.02 (0.005)
Product2	0.01 (0.003)	-1.18 (0.012)	-0.02 (0.003)	0.68 (0.011)	0.00 (0.003)	0.00 (0.003)	0.31 (0.008)
Product3	0.29 (0.007)	-0.02 (0.003)	-0.61 (0.014)	0.00 (0.003)	0.08 (0.008)	0.29 (0.007)	0.00 (0.003)
Product4	0.03 (0.004)	0.64 (0.010)	0.00 (0.003)	-2.33 (0.017)	0.01 (0.003)	0.00 (0.005)	0.88 (0.011)
Product5	2.44 (0.019)	0.01 (0.002)	0.10 (0.010)	0.01 (0.003)	-2.34 (0.019)	0.50 (0.010)	0.01 (0.004)
Product6	1.60 (0.007)	0.01 (0.002)	0.44 (0.004)	0.01 (0.003)	0.64 (0.007)	-1.87 (0.014)	0.04 (0.004)
Product7	0.03 (0.003)	0.53 (0.004)	0.00 (0.002)	1.61 (0.008)	0.01 (0.002)	0.04 (0.004)	-1.26 (0.010)

Notes: Standard error in parentheses.

Table A2. Own price and cross-price elasticities - 10% price decrease, model without RP.

	Product1	Product2	Product3	Product4	Product5	Product6	Product7
Product1	4.88 (0.029)	-0.03 (0.003)	-0.52 (0.008)	-0.04 (0.005)	-3.05 (0.018)	-1.06 (0.018)	-0.02 (0.006)
Product2	-0.03 (0.004)	1.73 (0.015)	0.01 (0.003)	-0.72 (0.013)	-0.01 (0.003)	-0.01 (0.004)	-0.32 (0.011)
Product3	-0.40 (0.011)	0.01 (0.003)	1.57 (0.019)	0.00 (0.003)	-0.34 (0.011)	-0.29 (0.010)	0.00 (0.004)
Product4	-0.04 (0.004)	-0.90 (0.010)	0.00 (0.003)	2.60 (0.020)	-0.02 (0.003)	-0.01 (0.006)	-0.90 (0.015)
Product5	-1.99 (0.027)	-0.01 (0.003)	-0.30 (0.009)	-0.02 (0.004)	4.90 (0.025)	-0.50 (0.015)	-0.01 (0.005)
Product6	-2.37 (0.007)	-0.01 (0.002)	-0.75 (0.004)	-0.01 (0.003)	-1.45 (0.006)	1.90 (0.013)	-0.04 (0.004)
Product7	-0.05 (0.003)	-0.78 (0.004)	-0.01 (0.002)	-1.81 (0.007)	-0.03 (0.002)	-0.05 (0.005)	1.30 (0.010)

Notes: Standard error in parentheses.

Table A3. Own price and cross-price elasticities - 10% price increase, model with RP.

	Product1	Product2	Product3	Product4	Product5	Product6	Product7
Product1	-5.75 (0.019)	0.03 (0.003)	0.43 (0.008)	0.03 (0.003)	2.13 (0.018)	1.20 (0.011)	0.02 (0.004)
Product2	0.03 (0.003)	-1.74 (0.011)	-0.01 (0.003)	1.08 (0.009)	0.01 (0.002)	0.00 (0.003)	0.35 (0.007)
Product3	0.64 (0.006)	-0.01 (0.004)	-1.17 (0.013)	0.00 (0.003)	0.24 (0.007)	0.33 (0.005)	0.00 (0.003)
Product4	0.03 (0.004)	1.09 (0.009)	0.00 (0.002)	-2.81 (0.015)	0.01 (0.003)	0.00 (0.005)	0.93 (0.011)
Product5	3.15 (0.015)	0.01 (0.002)	0.26 (0.008)	0.01 (0.003)	-3.12 (0.016)	0.58 (0.008)	0.01 (0.004)
Product6	1.86 (0.006)	0.01 (0.001)	0.49 (0.003)	0.01 (0.003)	0.73 (0.005)	-2.16 (0.012)	0.04 (0.003)
Product7	0.03 (0.002)	0.60 (0.004)	0.00 (0.002)	1.68 (0.008)	0.01 (0.002)	0.04 (0.004)	-1.36 (0.010)

Notes: Standard errors in parentheses.

A4.4. EASI demand system: Elasticities

Table A4. Own price and cross-price elasticities - 10% price decrease, model with RP.

	Product1	Product2	Product3	Product4	Product5	Product6	Product7
Product1	3.92 (0.023)	-0.02 (0.003)	-0.09 (0.006)	-0.03 (0.004)	-2.34 (0.015)	-1.02 (0.015)	-0.02 (0.005)
Product2	-0.02 (0.003)	1.20 (0.013)	0.02 (0.004)	-0.40 (0.012)	-0.01 (0.002)	-0.01 (0.004)	-0.30 (0.010)
Product3	-0.09 (0.009)	0.02 (0.003)	0.85 (0.015)	0.00 (0.003)	-0.18 (0.009)	-0.26 (0.007)	0.00 (0.003)
Product4	-0.03 (0.004)	-0.46 (0.008)	0.00 (0.002)	2.05 (0.019)	-0.01 (0.003)	0.00 (0.006)	-0.78 (0.014)
Product5	-1.47 (0.021)	-0.01 (0.002)	-0.10 (0.008)	-0.01 (0.003)	3.90 (0.021)	-0.47 (0.012)	-0.01 (0.004)
Product6	-2.27 (0.006)	-0.01 (0.002)	-0.68 (0.003)	-0.01 (0.003)	-1.33 (0.005)	1.80 (0.011)	-0.04 (0.004)
Product7	-0.05 (0.002)	-0.72 (0.003)	-0.01 (0.002)	-1.60 (0.007)	-0.02 (0.002)	-0.04 (0.004)	1.15 (0.009)

Notes: Standard error in parentheses.

Table A5. Own- and cross-price elasticities - EASI model without RP.

	Diet	SSBs<5	SSBs 5-8	SSBs>8	Water	Beer&C
Diet	-0.80 (0.017)	-0.17 (0.013)	-0.02 (0.006)	0.21 (0.006)	0.17 (0.005)	-0.09 (0.009)
SSBs<5	-0.02 (0.009)	-0.85 (0.006)	-0.02 (0.002)	0.42 (0.007)	0.06 (0.005)	0.08 (0.008)
SSBs 5-8	-0.02 (0.024)	-0.10 (0.012)	-0.67 (0.009)	0.06 (0.012)	-0.01 (0.012)	0.28 (0.012)
SSBs>8	0.23 (0.004)	0.36 (0.004)	0.00 (0.002)	-1.08 (0.010)	-0.08 (0.005)	0.16 (0.009)
Water	0.48 (0.013)	0.10 (0.016)	-0.03 (0.009)	-0.58 (0.028)	-1.15 (0.022)	0.14 (0.019)
Beer&C	-0.74 (0.016)	-0.65 (0.016)	-0.02 (0.005)	-0.54 (0.021)	-0.08 (0.010)	-1.41 (0.024)

Notes: Standard errors in parentheses.

Table A6. Own price and cross-price elasticities - EASI model with RP: Loss elasticities.

	Diet	SSBs<5	SSBs $5-8$	SSBs>8	Water	Beer&C
Diet	-1.04 (0.027)	-0.05 (0.030)	0.01 (0.010)	0.18 (0.027)	0.14 (0.010)	0.04 (0.025)
SSBs<5	0.03 (0.027)	-0.97 (0.023)	0.01 (0.005)	0.43 (0.018)	0.04 (0.008)	0.12 (0.014)
SSBs 5-8	0.06 (0.041)	-0.06 (0.023)	-0.86 (0.020)	0.08 (0.040)	-0.02 (0.019)	0.28 (0.035)
SSBs>8	0.17 (0.017)	0.39 (0.019)	0.03 (0.006)	-1.23 (0.007)	-0.09 (0.010)	0.27 (0.013)
Water	0.44 (0.032)	0.10 (0.034)	-0.02 (0.014)	-0.50 (0.047)	-1.36 (0.040)	0.36 (0.044)
Beer&C	-0.44 (0.046)	-0.67 (0.030)	-0.09 (0.012)	-0.30 (0.034)	0.05 (0.023)	-1.87 (0.033)

Notes: Standard errors in parentheses.

Table A7. Own price and cross-price elasticities - EASI model with RP: Gain elasticities.

	Diet	SSBs<5	SSBs 5-8	SSBs>8	Water	Beer&C
Diet	0.618 (0.022)	0.106 (0.020)	0.033 (0.009)	-0.081 (0.014)	-0.063 (0.015)	0.096 (0.018)
SSBs<5	-0.024 (0.017)	0.659 (0.015)	0.018 (0.005)	-0.210 (0.022)	-0.063 (0.012)	-0.038 (0.014)
SSBs 5-8	0.064 (0.033)	0.098 (0.021)	0.559 (0.008)	-0.092 (0.032)	0.014 (0.015)	-0.141 (0.035)
SSBs>8	-0.122 (0.010)	-0.125 (0.021)	-0.004 (0.005)	0.676 (0.034)	-0.030 (0.011)	0.039 (0.015)
Water	-0.110 (0.044)	0.008 (0.046)	0.046 (0.011)	0.126 (0.060)	0.673 (0.037)	0.258 (0.036)
Beer&C	0.683 (0.029)	0.569 (0.035)	0.038 (0.016)	0.921 (0.037)	0.321 (0.022)	0.831 (0.038)

Notes: Standard errors in parentheses.