Technical appendix: demand modelling strategy

The demand model applied was based on the linear version of Almost Ideal Demand System where expenditure shares are modelled as a function of prices and total expenditure (as an approximation for income) adjusted for all price levels:

$$w_{iht} = \alpha_i + \sum_{j=1}^{N} \gamma_{ij} lnp_{jht} + \beta_i \frac{lnx_{ht}}{P_{ht}} + \varepsilon_{iht} \qquad (1)$$

where:

w_{iht} is expenditure share of group *i* (i=1, 2, …, 11) for household *h* (h=1,2,…31,919) in month *t* (t=1, 2, …, 26)

lnx_{ht} is the log of total household monthly expenditure on beverages per capita

lnp_{jht} is the log of price for category *j* for household *h* in month *t*

$P_{ht}$is a Laspeyres price index of geometrically weighted average prices defined as $lnP = \sum_i \overline{w}_i lnp_i$

ε_{iht} is a random disturbance

To deal with zero observations (ranging from 15% for fruit juices, to over 50% for certain alcoholic beverages (e.g. cider)), that can bias the estimates, we followed a two-step procedure developed by Shonkweiler and Yen (1999) (SY).[1] The (SY) approach, while widely used and relatively easy to implement, has been criticised based on its reliance on the assumption of normality and homoscedasticity in model residuals. As an alternative, a semiparametric approach has been suggested by Sam and Zheng (2010) [2] which does not rely on assumptions about distribution. Given the relatively large number of beverage groups and number of households in the data, and that the semiparametric approach is computationally highly demanding [3-5] while has been shown to yield in robust estimates relative to SY estimates (despite deviance from the underlying assumptions) [3] we opt for the computationally less demanding SY approach but apply bootstrapped standard errors to derive elasticities (see below) [4,5].

Thus, in the first step, the decision to purchase beverages in any group was modelled as a function of lagged volume (in L) of beverages purchased in that group, household size, age of the main shopper, socio-economic group (A&B, C1&C2 or D&E), whether or not the household owns their house, income group (for the whole sample only), presence of children and time indicators to take into account seasonal trends, using a probit model. From the probit model, we estimated the probability density function (ϕ_i) and cumulative density function (Φ_i) of the linear predictions of the fitted model.

The second step second step of estimating the demand function (1) includes the (ϕ_i) and (Φ_i):

$$w_{iht}^{*} = \Phi_{iht}(w_{iht}) + \varphi_i \phi_{iht} + \sum_{t=1}^{13} \rho_{it} T_{it} + v_{ih} + \varepsilon_{it} \qquad (2)$$

Where additionally,

T_{it} are indicator variables to capture any seasonal or other time effects (13 four-week periods)

v_{ih} is a fixed household effect

For each beverage group i=1, 2 ,...,11 we estimated (2) equation-by-equation using a fixed effect model with robust clustered standard errors to allow for any misspecification, particularly serial correlation of observations within the households. Clusters were defined at the geographical area used in estimating prices (n=110).

The specification used (2) imposed the restrictions, compatible with the AIDS model, of adding-up $[\sum_{i=1}^{N} \alpha_i = 1;\ \sum_{i=1}^{N} \beta_i = 0]$ and homogeneity $[\sum_{i=1}^{N} \gamma_{ij} = 0]$.

There are two important sources of potential endogeneity in the model. First, total expenditure enters the model as a proxy for incomes while it is also used to calculate the expenditure shares). Furthermore, total expenditure might be endogenous because of possible correlation with unobserved characteristics affecting demand behaviour or because of shocks common to total expenditure and expenditure shares. Secondly, unit prices estimated from monthly aggregates of expenditure and volume are likely to be biased due to quality effects.[6] If prices or expenditures are correlated with the equation errors, estimators will be both biased and inconsistent.

To deal with quality effects in prices, we took the assumption that in a relatively small geographical area households face the same prices during the same time period. To estimate these geographical average unit values we calculated the monthly average prices for the (n=110) postcode areas which we observe in the data. Where the monthly price was missing (e.g. households did not purchase the products in this beverage group in a particular month), it was replaced by the first non-missing average of the previous and the following monthly prices. To reduce possible endogeneity between expenditure shares and total beverage expenditure we use the approach developed in [7] and regressed household per capita beverage expenditure on prices and household socio demographic characteristics (social class, income (whole sample only), whether or not the household owns their house and presence of children. The predicted values from the model were used as instruments for total expenditure.

To estimate unconditional elasticities (i.e. taking into account that the budget for beverages is dependent on rest of the foods purchased we estimated the first-stage demand for beverages as a function of aggregate beverage price, prices of other aggregate food groups (dairy & eggs, meat & fish, fruits & vegetables, ready meals & convenience foods, snacks and fats & starches), and total expenditure on foods and beverages, following the model specified in (2).

Uncompensated elasticities were estimated for beverages and individual beverage groups, including the censoring variable CDF at sample averages as follows:

$$e_{ij} = \Phi_i * \left(\frac{\gamma_{ij}}{w_i} - \frac{\beta_i w_j}{w_i}\right) - \Delta_{ij} \qquad (3)$$

Where Δ_{ij} is the Kronecker delta which equals 1 when i=j and 0 otherwise·

Expenditure elasticities were estimated by:

$$\epsilon_i = \Phi_i * \left(\frac{\beta_i}{w_i}\right) + 1$$

Finally, unconditional elasticities combining both levels of budgeting were estimated as in [8]:

$$e_{ij} = e_{ij|B} + w_j \left(\frac{1}{\epsilon_{j|B}} + \epsilon_B\right) \times \epsilon_{i|B}\epsilon_{j|B} + w_B w_j \epsilon_B \epsilon_{i|B} \times (\epsilon_{j|B} - 1)$$

Where: $e_{ij|B}$ is the price elasticity of beverages

$e_{ij|B}$ is the price elasticity of beverages in group i

ϵ_B is the expenditure elasticity of beverages

$\epsilon_{i|B}$ is the expenditure elasticity of beverages in group i

$\epsilon_{j|B}$ is the expenditure elasticity of beverages in group j

w_B is the average expenditure share of beverages in total food and beverage expenditure

w_j is the average expenditure share of beverage group j in total beverage expenditure.

Expenditure share equations in (2) are estimated with clustered (geographical area) robust standard errors to account for heterogeneity and standard errors for final unconditional elasticities are bootstrapped (250 replications). Elasticities in appendix 1 are reported bias-corrected confidence intervals. All analyses are done using Stata 15 [9] software.

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