THE HEALTH EFFECTS OF A FISCAL FOOD POLICY

Department of Food Economics and Marketing, University of Reading

Matthew J. Salois and Richard Tiffin

m.j.salois@reading.ac.uk

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Abstract

This paper examines the health effects of a fiscal food policy based on a combination of fat taxes and thin subsidies. The fat tax is based on the saturated fat content of food items while the thin subsidy is applied to select fruit and vegetbale items. The policy is designed to be revenue neutral so that the subsidy exactly offsets the revenue from the fat tax. A model of food demand is estimated using Bayesian methods that accounts for censoring and infrequency of purchase (the problem of unit values is also discussed). The estimated of demand elasticities are used to compute nutrient elasticities which demonstrate how consumption of specific nutrients changes based on price changes in particular foods from the fiscal policy. Results show that while the fat tax decreases saturated fat intake, consumption of other important nutrients is also decreased, which may lead to negative health outcomes.

JEL Codes: D30, D60, H20, I10, I30.

Keywords: Bayesian estimation, censoring, fat tax, infrequency of purchase, nutrient elasticities, obesity, thin subsidy, unit values.

1 Introduction

The prevalence of overweight and obesity in the UK has grown rapidly since the 1980s and, according to the Health Survey for England, in 2004 63% of the adult population had a BMI>25 while 24% were obese (BMI>30). There is accumulating evidence from the US that the upper half of the weight distribution has become larger; between the 1970s and 2000 median BMI among American adults increased from 24.6 to 26.3 (or by 8.9%), whereas the 95% percentile of the distribution rose from 33.9 to 39.6 (or by 16.8%). A similar shift in the shape of the distribution took place for American children (Anderson, Butcher and Levine, 2003). Similarly in England in the decade from 1993 to 2003, the upper part of the BMI distribution experienced significant BMI increases and the middle portion intermediate increases, while the lower tail remained largely unchanged (Wardle and Boniface, 2008).

Past information and education campaigns to improve healthy eating have proved ineffective in the UK (Foresight 2007). Officials across the medical and health community have made urgent calls for a more system-wide approach to dealing with the growing obesity epidemic (Marshall 2000; HCHC 2004; Gostin 2007). One element of such an approach that governments have considered is taxing unhealthy foods, so-called fat taxes, and/or subsidising healthy foods, so-called thin subsidies (Caraher and Cowburn 2005; Mytton et. al 2007; Brownell and Frieden 2009). The 'fat tax' concept is often dismissed as i) relatively ineffective because wealthy consumers are not very responsive to food prices, ii) regressive because poor consumers spend the largest share of their incomes on food, particularly 'cheap' energy-dense food, and iii) unfair because the tax falls on those who are not obese as well as on those who are.

Since a fat tax alone is inevitably highly regressive, recent proposals suggest combining it with a thin subsidy to encourage fruit and vegetable consumption. Poorer people are more responsive to prices (Deaton, 1997) and may increase their fruit and vegetable consumption substantially. The extent to which the tax and subsidy combination is effective is the empirical question addressed in this paper. A model of demand is estimated to obtain elasticity estimates, which are then used to simulate the effects of changes in the distribution of nutrient consumption in England resulting from the imposition of fat taxes and thin subsidies. In particular, a revenue neutral fiscal policy is developed where the fat-tax is imposed on certain foods based on saturated fat content while the thin-subsidy is placed selected fruits and vegetables groups. The estimated demand elasticities will determine the impact of the fiscal policy in terms of consumption changes while the nutrient elasticities will ascertain the impact of the policy on selected nutrient intakes.

The Almost Ideal Demand System (AIDS) model is estimated using cross-section data from the 2003-2004 UK Expenditure and Food Survey (EFS). Two critical problems involved with estimating a demand model are discussed in this paper: censoring and the use of unit values. This paper uses a recently developed Bayesian methods for estimating AIDS models using the IPM to handle censoring. The method developed by Deaton (1987, 1988, 1990) to correct for the bias when using unit values is discussed.

This paper is organized as follows. The next section describes the major conceptual issue involved with estimating a system of demand. The third section discusses the Bayesian IPM estimator. The fourth section discusses the Huang (1996) process of converting demand elasticities into nutrient elasticities. The data are discussed in the fifth section and the results are presented in section six. The final section concludes.

2 Conceptual Issues

2.1 Censoring

Micro-data are in general subject to the econometric problem of censoring. In demand analysis this arises because most households do not purchase all of the commodities available to them. Wales and Woodland (1983) introduce two econometric models for censored demand systems. They refer to the first model as the Kuhn-Tucker approach. As its name implies, it is based on the Kuhn-Tucker conditions for the consumer's optimisation problem. The econometric model is developed by adding a stochastic term to the utility function and as a result to the Kuhn-Tucker conditions. The conditions hold as an equality when an interior solution results and as an inequality when there is a corner solution. As a result, the likelihood function is of a mixed discrete-continuous form (Pudney 1989, p163) and is difficult to maximise for all but relatively small demand systems because of the numerical integration that is required in its evaluation. The intractability of the likelihood function has led to very few examples of the empirical implementation of the Kuhn-Tucker approach, one example is Phaneuf et. al (2000).

By contrast, the second model proposed by Wales and Woodland (1983), which they refer to as the Amemiya-Tobin approach, has been more widespread in the literature. This second strategy for handling censoring is an application of the Tobit model (Tobin 1958) as extended by Amemiya (1974) to the estimation of a system of equations. In this approach the demand model is derived without explicitly incorporating the non-negativity conditions. Instead these are added to the estimated model by truncating the distribution of the stochastic demand choices to allow for a discrete probability mass at zero. A number of strategies have been adopted to the estimation of the Amemiya-Tobin model. The direct estimation of the system by maximum likelihood has been problematic for reasons of computational complexity. Earlier attempts at the estimation of the Amemiya-Tobin model are therefore based on the two stage approach proposed by Heien and Wessells (1990) and developed by Shonkwiler and Yen (1999) which is itself an application of the Heckman (1979) method.

The two step approach can be considered a generalisation of the Amemiya-Tobin approach because it comprises two sets of equations: in addition to the censored equations, additional equations are used to model the censoring and this allows the possibility of a difference between the models which determine the censoring rule and the continuous observations. The generalisation of the Tobit model in this way is discussed in the context of demand for a single good by Blundell and Meghir (1987) who refer to the model in which the sample selection rule and the continuous variable models differ as the double hurdle model, a model introduced originally by Cragg (1971). The double hurdle model is adapted by Blundell and Meghir (1987) to form an infrequency of purchase model which addresses the fact that within a truncated survey period, observed purchases may differ from actual demand as stocks are either built up or run down. Yen et. al (2003) note that two step estimation is consistent but inefficient and they return to maximum likelihood estimation of the original Amemiya-Tobin model using simulated and quasi maximum likelihood methods. These methods are generalised in Stewart and Yen (2004) and Yen (2005) in an analogous way to the generalisation offered by the two step estimators referred to above to account for differences in the processes determining selection and the continuous variable. They recognise that this generalisation is the multivariate equivalent of that proposed by Cragg (1971). Their models are estimated by maximum likelihood and are thus efficient.

This paper is to contribute to this literature by applying Bayesian methods to the estimation of multivariate sample selection models. The range of models previously estimated by maximum likelihood ate extended hitherto to the infrequency of purchase model. The Bayesian method developed incorporates the Wales and Woodland (1983, p273) approach to the imposition of adding-up which, as Pudney (1989, p157) notes, has been problematic in a maximum likelihood context.

2.2 Unit-values

The EFS (like most household surveys) does not report prices, instead expenditure on each food item, the quantity of the item purchased, and the quarter the household was surveyed are reported. The unit value of each food item is derived by dividing expenditure by quantity. The unit value is not a price because, in addition to choosing the quantity of each food item they purchase, consumers also choose quality. Treating unit values as prices biases demand estimates. A method is needed for inferring the impacts of the unobserved prices on demand based on the unit value information available. In a series of articles Deaton (1987, 1988, 1990) shows that if it is a possible to identify a unit of observation within which prices faced by all consumers are the same, then the bias can be corrected. In Deaton's formulation, this unit is a geographical cluster of households.

The basic premise is a model of consumer behaviour in which households choose simultaneously how much of a commodity and of what quality to buy. The model specifies market prices as an endogenous variable that affects the quantities purchased, meaning market prices determine the observed unit values. The unit values include both measurement error and quality effects. The measurement error in the recording of expenditure and quantities, as well as the quality effect on the unit values, is taken into account in the model by spatially identifying the sample according to clusters. Households surveyed in the same geographic region at the same time are defined to be within the same cluster and, therefore, assumed to face the same price. Within-cluster variation in unit-values is used to estimate the influence of income (or total expenditure) and household characteristics on consumption and to estimate the degree of measurement error. Between-cluster variation in unit-values are due to spatial differences in prices and are used to estimate price elasticities.

In addition to complicated matrix multiplication, the main problem of applying Deaton's approach to estimating demand elasticities is that there is no guarantee of obtaining accurate estimates. Given that the residual covariance matrices S, R, Ω, and Γ are influenced by a variety of unexplained factors, price variation being just one possible factor, there is considerable imprecision to the Deaton approach. Moreover, recent studies have revealed the approach in Deaton (1990) does not correct for the biases resulting from using unit-values over market prices, and in some cases can be in even more severe than using unit-values in a traditional model (Brubakk 1997; Gibson and Rozelle 2005; Nimi 2005). The Deaton method is discussed in more detail in the appendix.

3 Infrequency of Purchase in the AIDS

The infrequency of purchase model is developed in order to accommodate the fact that censoring occurs in the demand system because a particular good may not be purchased by a household during the time that it is surveyed as it is consuming from stocks purchased in other time periods. Our approach draws on Blundell and Meghir (1987) in order to adapt the AIDS to incorporate infrequency of purchase. The censoring rule that relates latent consumption (q^*_{it})[1] of the i^{th} commodity by the h^{th} household to observed purchases (q_{ih}) is as follows:

$$q_{ih} = \begin{cases} \frac{q^*_{ih}}{\Phi_{it}} & y_{ih} = 1 \\ 0 & y_{ih} = 0 \end{cases}. \tag{1}$$

Φ_{ih} is the probability that a purchase is made $(p(y_{ih} = 1))$ and y_{ih} is a binary variable which takes the value 1 when a purchase occurs. The censoring rule (1) implies that there are two aspects to the latency of q^*_{ih} according to whether q_{ih} is observed or not. In cases where a purchase is made, latent consumption is related to observed purchases as follows:

$$q^*_{ih} = q_{ih}\Phi_{ih} \qquad \forall i \in C \tag{2}$$

[1] In this specification of the model we assume that latent consumption for all goods is non-zero. In other words we assume that all censoring is the result of infrequency of purchase. Whilst allowing for both infrequency of purchase and true corner solutions would be preferable, such an approach introduces an identification problem since the source of a zero may be either a non-purchase, a corner solution or both.

where:

$$C = \{i : y_{ih} = 1\}. \tag{3}$$

The latency in the observations where q_{ih} is observed is addressed in the AIDS by defining the consumption shares for observations where a purchase is observed as follows:

$$s_{ih} = \frac{p_{ih} q_{ih}^*}{\sum_{i \in C} p_{ih} q_{ih}^*} \qquad \forall i \in C \tag{4}$$

where p_{ih} is the price of the i^{th} good to the h^{th} household and q_{ih}^* is defined in equation 2.

In cases where no purchase is made q_{ih}^* is non-zero as the good in question is consumed from stocks. In this case latent consumption cannot be computed using (2) because q_{ih} is itself unobserved. Instead a data augmentation algorithm, which we discuss in section 4, is used to replace the observed zeros with estimated values for latent consumption. The shares computed using (4) for observations where a purchase is observed sum to one by construction and therefore once they are combined with the latent shares corresponding to observations where no purchase is made, the adding up restriction will be violated. Wales and Woodland (1983, p270) show how this problem can be addressed in a maximum likelihood context. In order to do this an additional source of latency is introduced into the model for the shares, defined in equation 4, where a purchase is made. The effect of this is to adjust the shares defined in equation 4 to ensure that the combined latent shares for goods where a purchase is made and those where one is not satisfy the adding up restriction. Thus we define latent shares for the cases where purchases are observed as follows:

$$s_{ih}^* = s_{ih} \left(1 - \sum_{i \notin C} s_{ih}^* \right) \ \forall i \in C \tag{5}$$

Pudney (1989) notes that implementing Wales and Woodland (1983) using maximum likelihood in systems with more than 3 commodities is computationally very expensive. This is because of the complex inter-dependencies which exist between the end points of the integrals in the likelihood function. The data augmentation algorithm which we employ does not entail any integration and it is therefore much less costly to implement [**?**] using our method.

The AIDS is then expressed in terms of the latent shares as follows:

$$\mathbf{s}^* = \mathbf{X}_1 \blacksquare + \mathbf{v} \tag{6}$$

where:

$$\mathbf{X}_1 = \mathbf{I}_m \otimes \mathbf{x}_1, \tag{7}$$

$$\mathbf{x}_1 = (\mathbf{x}_{11} \ldots, \mathbf{x}_{1H})', \tag{8}$$

$$\mathbf{x}_{1h} = \left(1, \ln p_{1,h}, \cdots, \ln p_{m+1,h}, \ln\left(\frac{e_h}{P_h}\right), D_h'\right)', \tag{9}$$

$$\mathbf{s}^* = (s^*_{1,1}, \cdots, s^*_{1,H}, s^*_{2,1}, \ldots, s^*_{2,H}, \ldots, s^*_{m,1}, \ldots s^*_{m,H})', \tag{10}$$

$$\blacksquare = \left(\alpha_1, \gamma_{11}, \ldots \gamma_{1,m+1}, \omega_1, \psi'_{1,}, \ldots, \alpha_m, \gamma_{m1}, \ldots \gamma_{m,m+1}, \omega_m, \psi'_{m,}\right)', \tag{11}$$

$$\mathbf{v} = (v_{1,1}, \cdots, v_{1,H}, v_{2,1}, \ldots, v_{2,H}, \ldots, v_{m,1}, \ldots v_{m,H})' \tag{12}$$

p_{jh} is the price of the j^{th} good to the h^{th} household e_t is total expenditure, $P_t = \prod_j p_{jh}^{s_{jh}}$ is Stone's price index and D_t is a vector of variables that describes demographic features of the h^{th} household.

The underlying theory requires that the model satisfies symmetry

$$\gamma_{ij} = \gamma_{ji} \text{ for all } i,j, \tag{13}$$

homogeneity

$$\sum_j \gamma_{ij} = 0 \text{ for all } j \tag{14}$$

and concavity. Concavity implies that the Slutsky matrix (**M**) which has the elements:

$$M_{ij} = \gamma_{ij} + \omega_i \omega_j \ln\left(\frac{e}{P}\right) - s_i \delta_{ij} + s_i s_j \tag{15}$$

$$\delta_{ii} = 1, \delta_{ij} = 0 : i \neq j \tag{16}$$

is negative semi-definite. The restrictions required for symmetry and homogeneity can be written in the form

$$\mathbf{R}\blacksquare^{*} = 0 \tag{17}$$

where $\mathbf{R}$ is an $r \times m(m+2)$ matrix defining the restrictions and $\blacksquare^{*}$ is the restricted Λ. In order to impose these restrictions we re-parametrize the model as follows. First define the $(km - r) \times km$ orthonormal matrix $\mathbf{R}_{\perp}$ such that:

$$\begin{aligned} \mathbf{R}\mathbf{R}'_{\perp} &= 0 & (18) \\ \mathbf{R}_{\perp}\mathbf{R}'_{\perp} &= \mathbf{I}. & (19) \end{aligned}$$

The restricted $\blacksquare$ can be expressed as:

$$\Lambda^{*} = \mathbf{R}'_{\perp}\tilde{\Lambda} \tag{20}$$

where $\tilde{\blacksquare}$ is a $(km - r) \times 1$ vector of distinct parameters. The restricted model can be written:

$$\begin{aligned} \mathbf{s}^{*} &= \mathbf{X}_1 \mathbf{R}'_{\perp}\tilde{\blacksquare} + \mathbf{v} & (21) \\ \mathbf{s}^{*} &= \mathbf{W}\tilde{\blacksquare} + \mathbf{v} & (22) \end{aligned}$$

where:

$$\mathbf{W} = \mathbf{X}_1 \mathbf{R}'_{\perp}. \tag{23}$$

Equation 22 is the basis for estimation and the restricted parameter vector is recovered using equation 20.

To complete the IPM, the demand equations in 6 are combined with m probit equations to give the complete model:

$$\mathbf{s}^* = \mathbf{W}\tilde{\Lambda} + \mathbf{v} \tag{24}$$

$$\mathbf{y}^* = \mathbf{X}_2\Gamma + \mathbf{u} \tag{25}$$

where $\mathbf{y}^*$ is an $mH \times 1$ vector of latent variables structured in the same way as $\mathbf{s}^*$ (see equation 10) and based on the binary variable y_{ih} defined in equation 1:

$$y_{ih}^* \begin{cases} > 0 & y_{ih} = 1 \\ \leq 0 & y_{ih} = 0 \end{cases}, \tag{26}$$

$$\mathbf{e} = \begin{pmatrix} \mathbf{v} \\ \mathbf{u} \end{pmatrix} \sim N\left(0, \Sigma \otimes \mathbf{I}_H\right), \tag{27}$$

and

$$\mathbf{X}_2 = \mathbf{I}_m \otimes \mathbf{x}_2 \tag{28}$$

$$\mathbf{x}_2 = \left(\mathbf{x}_{21} \ldots, \mathbf{x}_{2H}\right)' \tag{29}$$

is a matrix of variables that describe household specific characteristics which are assumed to determine the probability of the household making a purchase in a given time period.[2] In our application we assume that all households are identical in this respect and stocks are exhausted in a purely random manner. $\mathbf{x}_2$ is therefore a vector of constants. Since the

[2]The stochastic specification of our IPM differs slightly from that of Blundell and Meghir (1987) who explicitly allow for errors in both the decision about whether to consume and the decision about how much to consume. We implicitly assume that both sources of error are represented by the residuals in $\mathbf{v}$.

dependent variables in the probit equations (25) are unobserved, data augmentation is also used in their estimation. With the introduction of the probit equations the probability that is necessary for the computation of the latent shares in equation 2 can be obtained as:

$$\Phi_{ih} = p\left(y_{ih} = 1\right) = p\left(y^{*}_{ih} > 0\right) = p\left(u_{ih} > -\mathbf{x}_{2h}\Gamma_{i}\right) = \Phi\left(\mathbf{x}_{2h}\Gamma_{i}\right) \tag{30}$$

where Γ_i is the sub-vector of Γ corresponding to the i^{th} probit equation.

4 Bayesian Inference

We apply Bayesian inference to the parameters of the model by sampling from the posterior distribution of the parameters in the model and presenting the summary statistics of this sample. The Gibbs sampler (see Casella and George 1992) allows one to sample from a marginal distribution by using the conditional distributions of the parameters. In most applications parameters are grouped into blocks and the conditional distributions for these blocks are used as the basis for the sampler. If the dependent variables in 24 and 25 were observable, the full system comprising both sets of equation could be treated as a set of seemingly unrelated equations (SUR) and estimation using a Gibbs sampler would be straightforward. Writing the complete system in 24 and 25 as:

$$\mathbf{z}^{*} = \mathbf{X}\beta + \mathbf{e} \tag{31}$$

where:

$$\mathbf{z}^{*} = \left(\mathbf{s}^{*\prime}, \mathbf{y}^{*\prime}\right)^{\prime}, \mathbf{X} = \begin{pmatrix} \mathbf{W} & 0 \\ 0 & \mathbf{X_2} \end{pmatrix}, \beta = \left(\tilde{\blacksquare}^{\prime}, \blacksquare^{\prime}\right)^{\prime}. \tag{32}$$

Assuming a diffuse prior (Zellner (1971, p.241):

$$p\left(\beta,\Sigma^{-1}\right)=p\left(\beta\right)p\left(\Sigma^{-1}\right)\propto\left|\Sigma^{-1}\right|^{-\left(\frac{m+1}{2}\right)} \tag{33}$$

the conditional posterior distributions for the two blocks of parameters β and $\blacksquare$ are:

$$p\left(\beta|\mathbf{z},\mathbf{X},\blacksquare\right)\sim MVN\left(\left(\blacksquare^{-1}\otimes\mathbf{X}'\mathbf{X}\right)^{-1}\left(\blacksquare^{-1}\otimes\mathbf{X}'\right)\mathbf{z}^{*},\blacksquare^{-1}\otimes\mathbf{X}'\mathbf{X}\right) \tag{34}$$

$$p\left(\blacksquare|\mathbf{y},\mathbf{X},\beta\right)\sim IW\left(\tilde{\mathbf{e}}'\tilde{\mathbf{e}},H\right) \tag{35}$$

where:

$$\tilde{\mathbf{e}}=\begin{pmatrix} v_{1,1} & \dots & v_{m,1} & u_{1,1} & \dots & u_{m,1} \\ \vdots & & \vdots & \vdots & & \vdots \\ v_{1,H} & \dots & v_{m,H} & u_{1,H} & \dots & u_{m,H} \end{pmatrix} \tag{36}$$

As has been stated above, the theoretically derived property of concavity requires that the Slutsky matrix of the cost function (see equation 15) to be negative semi-definite. This is incorporated in the estimation by introducing an informative prior in the form of an indicator function which takes the value one when the parameter vector β leads to a negative semi-definite Slutsky matrix and zero otherwise. In practice this results in an accept:reject step in the algorithm in which only those draws on the distribution in equation 34 which satisfy this restriction are retained in the sample that is used for inference.

We have noted above that some elements of $\mathbf{z}^{*}$ are not observed however. In order to complete the algorithm we therefore employ data augmentation. Data augmentation was introduced by [**?**] as a method for conducting inference on the full posterior in the presence of latent data. Albert and Chib (1993) show how data augmentation can be accomplished using the Gibbs sampler. They show that where the conditional distributions of the latent data can be obtained, these data can be treated as another block of unknowns in the algorithm. In section 3 we argued that there were three types of latency in our model. The first type of latency is common to all limited dependent variable models and is referred to as missing data. In our model we have two types of missing data. In the share equations, where no purchase is made the shares are missing. In the probit equations the continuous variable $\left(y_{ih}^{*}\right)$ which underlies the observed binary variable is missing. The remaining two sources of latency apply to the observations where a purchase is made. In these cases latency exists first because the observed purchases do not correspond to actual consumption and second because the adding up restriction will not hold once consumption of the commodities where no purchase is made is accounted for. In all three cases the conditional distributions of the latent data are used in the algorithm to simulate values.

Let us turn to the derivation of these distributions. First consider the conditionals for the missing data. Because the observations for individual households are assumed to be independent we can make the latent draws household by household. In order to introduce the conditional distributions therefore we define $\mathbf{z}_h^*$ and $\hat{\mathbf{z}}_h^*$ to include only the elements of $\mathbf{z}^*$ and $\hat{\mathbf{z}}^* = \mathbf{X}\beta$ respectively corresponding to the h^{th} household. It is also more convenient to draw the latent variables commodity by commodity. Therefore, defining the precision matrix $\blacksquare = \blacksquare^{-1}$, the conditional mean (μ_{ht}) and variance (V_i) of the individual elements of $\mathbf{z}^*$are Gweke (2005, Theorem 5.3.1):

$$\mu_{ih} = \hat{z}_{ih}^* + \blacksquare_i \blacksquare_{-i}^{-1}\left(\mathbf{z}_{-i,h}^* - \hat{\mathbf{z}}_{-i,h}^*\right) = \hat{z}_{ih}^* - \Omega_{ii}^{-1}\Omega_{-i}\left(\mathbf{z}_{-i,h}^* - \hat{\mathbf{z}}_{-i,h}^*\right) \quad (37)$$

$$V_i = \Sigma_{ii} - \blacksquare_i \blacksquare_{-i}^{-1} \blacksquare_i^{\prime} = \blacksquare_{-i}^{-1} \quad (38)$$

where Σ_{ii} is the i^{th} on-diagonal element of $\blacksquare$, $\blacksquare_i$ is the i^{th} row of $\blacksquare$ excluding Σ_{ii}, and $\blacksquare_{-i}$ is the matrix within $\blacksquare$ excluding both the i^{th} column and i^{th} row. Ω_{ii} and $\blacksquare_i$ are similarly defined. $\hat{z}_{it}$ is the fitted value of z_{ih} for the h^{th} household and $\hat{\mathbf{y}}_{-i,h}$ and $\mathbf{y}_{-i,h}$ are vectors within $\hat{\mathbf{y}}_h$ and $\mathbf{y}_h$ respectively, with their i^{th} elements removed. The conditional distributions for the missing data in the probit equations are:

$$
\begin{aligned}
y_{ih} &= 0 : y^*_{ih}|\mathbf{y}^*_{-i,h},\beta,\mathbf{X},\blacksquare \sim \mathbf{N}(\mu_{ih},V_i)\, I_{[-\infty,0]}\forall i,h && (39)\\
y_{ih} &= 1 : y^*_{ih}|\mathbf{y}^*_{-i,h},\beta,\mathbf{X},\blacksquare \sim \mathbf{N}(\mu_{ih},V_i)\, I_{[0,\infty]}\forall i,h && (40)
\end{aligned}
$$

and in the share equations:

$$
s_{ih} = 0 : s^*_{ih}|\mathbf{y}^*_{-i,h},\blacksquare,\mathbf{X},\blacksquare \sim \mathbf{N}(\mu_{ih},V_i)\, I_{[0,1]}\forall i \notin C,h \tag{41}
$$

where $I_{[-\infty,0]}$ is an indicator variable that is one if $y_{it} \in [-\infty,0]$ and zero otherwise and $I_{[0,1]}$ is similarly defined on the interval from zero to one.

For the remaining two types of latency, in observations where a purchase is made, the latent data are a linear transformation of the observed data. This data can therefore be simulated by applying the transformations in 2 and 5 sequentially to the observed data. It can be seen that because our method simulates the latent data and estimates the model directly using these data it greatly simplifies the Wales and Woodland (1983, p270) approach to ensuring that adding up is satisfied by the latent shares in comparison with maximum likelihood.

The remaining issue we shall discuss is the identification of the probit equations. To achieve this it is necessary to restrict the covariance matrix:

$$
\blacksquare = \begin{pmatrix} \blacksquare_{vv} & \blacksquare_{vu} \\ \blacksquare_{uv} & \blacksquare_{uu} \end{pmatrix}. \tag{42}
$$

and we impose the restriction that $\blacksquare_{uu} = \mathbf{I}$. Instead of using equation 35 as the basis for making draws on Σ, we obtain the conditional posterior distributions for the sub-matrices within $\blacksquare$ as follows. Define the following $H \times m$ matrices:

$$\widetilde{\mathbf{v}} = \begin{pmatrix} v_{11} & v_{21} & \cdots & v_{m1} \\ \vdots & \vdots & & \vdots \\ v_{1H} & v_{2H} & \cdots & v_{mH} \end{pmatrix} \tag{43}$$

$$\widetilde{\mathbf{u}} = \begin{pmatrix} u_{11} & u_{21} & \cdots & u_{m1} \\ \vdots & \vdots & & \vdots \\ u_{1H} & u_{2H} & \cdots & u_{mH} \end{pmatrix} \tag{44}$$

From the properties of the multivariate normal the conditional mean and variance are:

$$E(\mathbf{v}|\mathbf{u}) = \Sigma_{vu}\Sigma_{uu}^{-1}\mathbf{u} \tag{45}$$

$$E\left(\mathbf{v}'\mathbf{v}|\mathbf{u}\right) = \blacksquare_{\varepsilon} = \Sigma_{vv} - \Sigma_{vu}\Sigma_{uu}^{-1}\Sigma_{vu}' \tag{46}$$

where 45 is a regression of $\mathbf{v}$ on $\mathbf{u}$. Under the assumption that $\Sigma_{uu} = \mathbf{I}$ we can therefore re-parametrize the covariance matrix as:

$$\blacksquare = \begin{pmatrix} \blacksquare_{vv} & \blacksquare_{vu} \\ \blacksquare_{uv} & \blacksquare_{uu} \end{pmatrix} = \begin{pmatrix} \left(\blacksquare_{\varepsilon} + \rho\rho'\right) & \rho \\ \rho' & \mathbf{I} \end{pmatrix}. \tag{47}$$

where $\rho = \Sigma_{vu}$. Recognizing from equations 45 and 46, with the assumption $\Sigma_{uu} = \mathbf{I}$, that ρ and Σ_{ε} are the coefficient vector and covariance matrix of the error term ε respectively in the following seemingly unrelated regression:

$$\mathbf{v} = \rho\mathbf{u} + \varepsilon \tag{48}$$

$\varepsilon \sim N(0, \Sigma_\varepsilon)$ and assuming a diffuse prior we use the following conditional posteriors:

$$\rho | \blacksquare_\varepsilon \sim N\left[\left(\widetilde{\mathbf{u}}' \blacksquare_\varepsilon^{-1} \widetilde{\mathbf{u}} \right)^{-1} \widetilde{\mathbf{u}}' \widetilde{\mathbf{v}},\, \left(\widetilde{\mathbf{u}}' \blacksquare_\varepsilon^{-1} \widetilde{\mathbf{u}} \right)^{-1} \right] \tag{49}$$

$$\blacksquare_\varepsilon | \delta \sim IW(\varepsilon' \varepsilon, H) \tag{50}$$

together with the relations in 47 as the basis for sampling the restricted covariance matrix.

The estimation algorithm can then be stated as:

1. Assume starting values for $\mathbf{z}^*$ and Σ.

2. Use the most recently drawn values of $\mathbf{z}^*$ from steps 4 and 5 and Σ from step 6 (or those assumed in step 1 if this is the first pass), draw the parameter vector β from the normal distribution in equation 34.

3. Use the appropriate elements of the β draw to compute the Slutsky matrix using equation 15 and check to see whether it is negative semi-definite. If it is, add the draw to the sample. If it is not revert to the previous draw of β.

4. Using the parameter vector drawn in 2, compute $\hat{\mathbf{z}}^* = \mathbf{X}\beta$. Using the appropriate elements in $\hat{\mathbf{z}}^*$ and Σ from step 6 (or that assumed in step 1 if this is the first pass), compute the mean and variance of the conditional distributions using equations 37 and 38. Use these in the truncated normal distributions in equations 39 and 40 to draw the latent data for the probit equations.

5. Obtain the latent data for the share equations:

   (a) Where the share is censored use the appropriate elements in $\hat{\mathbf{z}}^*$ from step 4 and Σ from step 6 (or that assumed in step 1 if this is the first pass) to compute the mean and variance of the conditional distribution using equations 37 and 38. Use these to make a draw on the distribution in equation 41.

(b) Where a purchase is observed compute the probability of a purchase using equation 30 and the latent shares using equations 4 and 5.

6. Using β from step 2 and $\mathbf{z}^*$ from steps 4 and 5, draw the variance-covariance matrix $\blacksquare$:

   (a) Draw ρ from the normal distribution in equation 49.

   (b) Draw $\blacksquare_\varepsilon$ from the inverse Wishart distribution in equation 50.

   (c) Construct the complete matrix using equation 47.

7. Return to step 2.

5 Converting to Nutrient Elasticities

The main objective of this paper is to determine the health effects of a fiscal food policy. Once the matrix of price elasticities is computed, corrected for quality effects and measurement error, the next step is compute the nutrient elasticities. The nutrient elasticities provide information on how intake of specific nutrients, such saturated fat or protein, may change as a result of a combination of fat taxes and thin subsidies. The technique developed by Huang (1996,1999) is used to link the demand model to nutrient availability. The basic premise of the approach in Huang (1996) is that changes in the price of a particular food or in total expenditure will affect the consumption of all food items and will simultaneously change intakes in a variety of different nutrients. Three pieces of information are needed: the expenditure elasticities, price elasticities, and the nutrient values of each food.

Define a_{ki} as the amount of the k^{th} nutrient obtained from a unit of the i^{th} food and let ϕ_k be the total amount of that nutrient obtained over the different food items consumed. An expression for ϕ_k is given by

$$\phi_k = \sum_i a_{ki} q_i, \tag{51}$$

where $k = 1,...,K$ is the total number of nutrients and q_i is the quantity demanded (i.e., the Marshallian demand) of the i^{th} food. Since demand is a function of prices (p) and expenditure (m), the Marshallian demand function is represented by $q_i = f(p,m)$. Changes in nutrient availability can therefore be expressed as

$$d\phi_k = \sum_i a_{ki} \left[\sum_j \frac{\partial q_i}{\partial p_i} dp_j + \frac{\partial q_i}{\partial m} dm \right]. \tag{52}$$

The relative change in nutrient availability can also be expressed in terms of relative changes in food prices and per capita expenditure as

$$\frac{d\phi_k}{\phi_k} = \sum_j \left(\sum_i \varepsilon_{ij} a_{ki} \frac{q_i}{\phi_k} \right) \left(\frac{dp_j}{p_j} \right) + \left(\sum_i \eta_i a_{ki} \frac{q_i}{\phi_k} \right) \left(\frac{dm}{m} \right), \tag{53}$$

where ε_{ij} denotes price elasticities and η_i denotes expenditure elasticities.

Equation 53 is equivalently written as

$$\frac{d\phi_k}{\phi_k} = \left(\pi_{kj} \frac{dp_j}{p_j} \right) + \left(\rho_k \frac{dm}{m} \right), \tag{54}$$

where π_{kj} is a price elasticity measure that relates the effect of a price change in the j^{th} food on the availability of the k^{th} nutrient, and ρ_k is an income elasticity measure that relates the effect of a change in total expenditure on the availability of that specific nutrient. The calculation of the nutrient elasticities represents a weighted average of the price and expenditure elasticities, with weights expressed as each food's share in the contribution to the k^{th} nutrient.

In practice, the calculation of the $K \times (G+1)$ matrix of nutrient elasticities (NE) for the case of K nutrients and G foods is obtained by multiplying the $K \times G$ nutrient share matrix of each food (NS) by the $G \times (G+1)$ matrix of food demand elasticities (FE)

$$NE = NS \times FE. \tag{55}$$

Based on the measurements of nutrient elasticity, a change in the price of a food or in per capita expenditure will affect all food quantities demanded through the interdependent demand relationships, resulting in simultaneous changes in the levels of nutrient availability (Huang 1996).

6 Data and Results

Data on food expenditures and quantities are from the UK government's Expenditure and Food Survey (EFS) for 2003-2004, which records data on a wide range of food eaten. The EFS (starting in 2001-2002) is the result of the merger between the Family Expenditure Survey (FES) and the National Food Survey (NFS), two well established surveys and important sources of information for government and the broad research community on UK spending and food consumption patterns. In this paper, the 2003-2004 data set is used, which is the latest (at the time of starting to work with the data) complete data set available from the Economic and Social Data Service (ESDS). The 2003-2004 sample is based on 7,014 households in 672 postcode sectors stratified by Government Office Region in England and Wales. Participating households voluntarily record food purchases for consumption at home for a two week period using a food diary for each individual over seven years of age. Three key aspects to the data require special attention and include the food aggregations necessary for demand analysis, the nutrient content of aggregated food groups, and the calculation of the tax-subsidy policy instrument.

Individual food items are converted into aggregate food groups that can be identified for a fat tax or thin subsidy. Seven main food groups are: dairy and eggs, meat and fish, staples and starches, fruits and vegetables, fats and sugars, drinks, and hot takeaway. Each main food groups is composed of sub-food groups (29 in total) listed in the first two columns of Table 1 (a complete listing of the individual food items used in each level of aggregation is available upon request). While broad aggregates simplify the analysis, detailed information is inevitably lost in the aggregation process. For example, the "milk" category includes both full-fat and skimmed milk, and the price elasticities may potentially differ between these two sub-category items.

Table 1 also presents the household averages for quantity consumed, unit value, and budget share for the sub-food groups. Mean quantities consumed per household are in kilogrammes or litre equivalent and unit values per household are in GBP per kilogram or litre equivalent (except eggs, which are in pence per unit). Meat and fish compose the largest share of the average household budget at about 22 percent. This is followed by drinks and fruits and vegetables both at 16 percent, fats and sugars at 15 percent, dairy and eggs at 14 percent, staples and starches at 12 percent, and hot takeaway at 5 percent.

The data in the EFS that is publicly accessible only provides data for the survey household by Government Office Region (GOR) and by survey quarter. Since there are only four quarters in the survey year and nine GORs, the publicly available data only permit 48 distinct clusters to be defined. While this does allow for the estimation of elasticities for reasonable small demand system, the small cluster number of clusters creates problems in the between-cluster estimation stage in the Deaton approach.

6.1 Nutrient contents

The EFS data provide the nutrient contents of 45 different nutrients for each individual food item. Table 2 shows the nutritive values for the 29 sub-food groups for selected nutrients (the full nutrient content of the food groups for all 45 nutrients is available upon request). Food energy is measured in food calories (kcal); protein, fat, and carbohydrates in grams; and calcium and iron in milligrams. The nutritive content provided is per gram or millitre equivalent of the respective food item (except eggs which is given per a medium size egg). The food items that tend to contain the most energy per unit include (excluding eggs): all fats; biscuits, cakes, and pastries; candies and other sugars; breakfast cereals; other starches and staples; and cheeses. The food energy contents of these groups are related to higher food nutrient contents of protein, fats and carbohydrates.

For example, cheese has high contents of both animal protein and fats, but is low in carbohydrates. Breakfast cereals and other starches and staples have high carbohydrate content, but are lower in protein and fat. The fruit and vegetable sub-food groups are higher in calcium and vegetable proteins than most of the other groups, but are generally lower in total energy. The other fruits and vegetables category is an exception as these items correspond to fruit and vegetable based ready-made meals and other takeaway products, which are higher both in total energy and in saturated fats. The meat products are both high in animal proteins and total energy and in the case of beef, pork, and lamb, are also high in saturated fats

By multiplying the amount of each sub-food group consumption by its nutritive values the food shares of nutrients are obtained. The share matrix is presented in Table 3, which is also the S matrix used in the Huang (1996) approach to obtain the nutrient elasticities. Total energy consumption is mostly derived from breads, all fats, biscuits, cakes and pastries, candies and other sugars, and tea and coffee, which together contribute nearly 50 percent to total energy intake. The fruit and vegetable food groups contribute very little to overall energy intake at less than 7 percent. Combined consumption of milk and cream, all fats, and biscuits, cakes, and pastries give most of the nutritive content of saturated fat (42 percent). Carbohydrates are mostly obtained from breads (20 percent), though biscuits, cakes, and pastry yield another 10 percent. Calcium intake is mostly based from milk and cream (27 percent) and bread (15 percent).

6.2 The fiscal food policy

The fat tax applied to selected food groups is based on saturated fatty acid content. The subsidy is applied to most of the fruit & vegetable groups, except the one-a-day and other fruits and vegetables group. The one-a-day group is excluded since intake of each of the food items in this group only count once for the recommended servings of fruits and vegetables. The other fruits and vegetables group is excluded because these items consist of ready-made meals and other takeaway products and contain relatively higher quantities and are actually taxed.

The fiscal policy used, based on a combination of taxes and subsidies, is designed to be a revenue-neutral scheme. The choice of saturated fatty acids as the prime target of the fat tax is justified by evidence from the medical literature. Saturated fats are an important risk factor in the occurrence of coronary heart disease (Hu et al. 1997), higher systolic blood pressure (Esrey et al. 1996), and higher plasma concentration of cholesterol (Ascherio et al. 1994). Fruit and vegetables, on the other hand, are positively linked to lower risks of various cancers (Ames et al. 1995; Riboli and Norat 2003), major chronic diseases (Hung et al. 2001), and ischaemic stroke (Joshipura et al. 2001).

Specifically, the fiscal scheme simulation increases the price of each food group by 1% for every percent of saturated fats the group contains. The EFS data set contains nutrient conversion tables that are used to convert food group items into nutrient content. For example, since milk contains 1.72% of saturated fats, its price increasing by 1.72%. A ceiling of 15% is placed on the simulated price increase. To offset this tax burden, and to encourage the consumption of fruit and vegetables, a subsidy on fruit and vegetables is introduced, so as to exactly cancel the costs of the fat tax paid by consumers. Table 4 presents the tax and subsidy rates applied to the different component food group items and assigns an index number to each group.

6.3 Demand Elasticity Estimates

The demand elasticities computed for this paper contain 870 estimates of own- and cross-price elasticities and expenditure elasticities for 29 food groups. Only the own-price and expenditure elasticities obtained from the alternative demand approach are listed in Table 5.

All of the estimated own-price elasticities are statistically significant and have the expected negative sign. A number of the food groups are price elastic (i.e., have an own-price elasticity greater than unity) and include other meats, other staples/starches, frozen fruits/vegetables, other fruits/vegetables, water, and hot takeaway. Of particular interest is the fact that the “other” food categories for meats, staples/starches, and fruit/vegetables all include ready-made and cold takeaway items. The smallest own-price elasticities (less than 0.7) are found for cheeses, milk/cream, fish, and all fats, which are all relatively inelastic. The own-price elasticities for eggs, breads, breakfast cereals, rice/pasta, and biscuits, cakes, and pastry are also generally of small magnitude indicating relative in elasticity. The remaining food categories are very close to being unit-elastic.

In terms of the expenditure elasticities, all are positive and statistically significant. While most of the expenditure elasticities are less than one, a few food groups are associated with being superior goods such as other dairy, other meats, other staples/starches, other fruits/vegetables, fresh fruits/vegetables, alcohol, water, and hot takeaway. Again, the “other” products include ready-made products and cold takeaway items. For example, other dairy is composed of, among other items, ice cream, milk puddings, and takeaway products such as milkshakes. Moreover, those food items with expenditure elasticities greater than one also have own-price elasticities greater than, or close to, one as well (except the biscuits, cakes, and pastry group). The smallest expenditure elasticities (less than 0.6) are for eggs and tinned/processed fruits and vegetables.

6.4 Nutrient Elasticity Estimates

Using the estimated demand elasticities and the food shares of nutrients contained in Table 3, nutrient elasticities are calculated on the basis of equation 55. The following tables provide estimates for the nutrient elasticities of each specific food group:

Table 6 lists the nutrient elasticities for the dairy and eggs food groups.

Table 7 lists the nutrient elasticities for the meat and fish food groups.

Table 8 lists the nutrient elasticities for the staples and starches food groups.

Table 9 lists the nutrient elasticities for the fruits and vegetables food groups.

Table 10 lists the nutrient elasticities for the fats and sugars food groups.

Table 11 lists the nutrient elasticities for the drinks food groups.

Table 12 lists the nutrient elasticities for hot takeaway.

The reported nutrient elasticities show the effect of a 1% increase in price or total expenditure on a selection of 45 different nutrients. For example, a 1% increase in the price of cheese (holding other prices and income constant) will affect the amount of all food consumption through the interdependent demand relationships. Changes in food consumption resulting from a 1% price increase in cheese will, for example, reduce per capita energy by 0.034%, saturated fat intake by 0.086%, and lactose by 0.15%. From our fiscal food policy in Table 4, a fat-tax based on saturated fat content would suggest a 15% increase in the price of cheese. If the price of cheese is expected to rise one-for-one with the fat-tax then per capita energy would in fact be reduced by 0.51% (i.e., 0.034% multiplied by 15%) and saturated fat intake would fall by 1.29%. The impact of the food price changes from the fiscal policy in Table 4 can be obtained in a similar way.

From a diet and health perspective of keen interest is the suggested fat tax on cheeses (already discussed) and on the foods in the fats and sugars groups, which had the heaviest tax levied on them due to their high saturated fat content. For example, the 15% tax on all fats would result in a drop in saturated fat intake 1.83% and total energy by 1.13%. Given that dairy products and foods in the fats and sugars group compose a large share of both average per capita intakes of saturated fats and total energy, any tax is likely to reduce not only fat intake, but also total energy intake as well. Moreover, intake of important nutrients will also fall as a result of a fat-tax. For example, the tax on all fats will reduce vitamin D intake by 2.58% and vitamin E by 4.41%, which are non-trivial changes in the average diet.

The tax on biscuits, cakes, and pastry reduces saturated fat intake by 0.89% but also reduces carbohydrate intake by 1.00%.

Looking at the impact of the subsidies on selected fruits and vegetables foods also yields interesting changes in nutrient consumption. The suggested subsidy on fresh fruits and vegetables will, for example, increase intake of important nutrient substantially such as carotene (15.79%), vitamin C (9.23%), dietary fibre (4.42%), and vitamin E (2%). On the other hand, intake of certain sugars increases as well including glucose (5.49%) and fructose (7.92%). In addition, since fresh fruits and vegetables compose only a very small share of energy intake, the subsidy only increases total energy by 0.80%. The subsidies on both frozen and tinned/processed fruits and vegetables follow similarly, though the changes are of much smaller magnitude given they contain less nutrients than fresh fruits and vegetables. For example, the subsidy on frozen fruits and vegetables increases carotene by 2.16%, vitamin C by 1.20%, dietary fibre by 0.88% and vitamin E by 0.11%. Energy intake from the subsidy on frozen fruits vegetables only increases by 0.08%.

7 Conclusions

Obesity is of increasing concern throughout the developed world. Some estimates suggest that by 2015, 60% of men and 50% of women will be obese. Being obese increases the risks of a range of chronic health problems including heart disease, type 2 diabetes and high blood pressure. Additionally it has been shown that increased levels of fruit and vegetable consumption will contribute to a reduction in the incidence of some cancers. As a result, there is an increase in interest in public health policies that are designed to reduce the impacts of diet related disease. One such policy is a fiscal intervention designed to reduce the consumption of calorie and fat dense food via a fat-tax and to encourage the consumption of fruit and vegetables via a thin susbsidy.

The extent to which a fiscal food policy is effective can be judged based on if the policy successfully redistributes consumption away from unhealthy foods towards healther food choices. Of particular importance is not just how consumption of specific food items shifts, but how changes in nutrient consumption are affected by a policy of food taxes and subsidies. This paper explores the linkage between food choice and nutrient consumption as the demand for food items shifts because of price changes.

Demand elasticities are obtained from a theoretically consistent demand model that accounts for censoring that occurs in most consumer surveys. This paper demonstrates how the infrequency of purchase model can be estimated for a system of equations using Monte Carlo Markov chain methods. The method was illustrated by estimating a model which is designed to disentangle the impacts of economic factors from preference heterogeneity resulting from differing demographic conditions in influencing the healthiness of diets in England and Wales.

The demand elasticities are then used to calculate nutrient elasticities which describe how nutrient consumption changes due to price changes in specific food groups. While the fat tax seems to be effective in reducing the average intake of saturated fats, there are negative consequences. Given that the groups with the highest fat tax rate applied to them account for the largest share of energy intake in the average UK diet, total energy intake declines as a result of the tax. Moreover, the fat tax also results in decreased consumption of important nutrients such as dietary fibre, and vitamins A, D, and E. The thin subsidy does appear to increase consumption of fruits and vegetables and therefore increase consumption of key nutrients, like carotene, sugar intake also increases substantially. Further, since energy supply from fruits and vegetables does not account for a large share of total energy supply, the decrease in calorie intake resulting from the tax is not fully compensated for by the subsidy on fruit and vegetable items.

References

[1] Albert, J.H., and S. Chib. (1993). Bayesian analysis of binary and polychotomous response data. *Journal of the American Statistical Association*, 88: 669-679.

[2] Amemiya, T. (1974). Multivariate regression and simultaneous equation models when dependent variables are truncated normal. *Econometrica*, 42(6): 999-1012.

[3] Ames, B.N., and L.S. Gold, and W.C. Willett. (1995). The causes and prevention of cancer. *Proceedings of the National Academy of Sciences*, 92(12): 5258-5265.

[4] Ascherio, A., C.H. Hennekens, J.E. Buring, C. Master, M.J. Stampfer, and W.C. Willet. (1994). Trans-fatty acids intake and risk of myocardial infarction. *Circulation*, 89(1): 94-101.

[5] Blundell, R., and C. Meghir. (1987). Bivariate alternatives to the Tobit model. *Journal of Econometrics*, 34(1-2): 179-200.

[6] Brownell, K., and T. Frieden. (2009). Ounces of prevention - the public policy case for taxes on sugared beverages. *New England Journal of Medicine*, 360(18): 1805-1808

[7] Caraher, M., and G. Cowburn. (2005). Taxing food: implications for public health nutrition. *Public Health Nutrition*, 8(8): 1242-1249.

[8] Casella, G., and E.I. George. (1992). Explaining the Gibbs sampler. *American Statistician*, 43(3): 167-174.

[9] Cragg, J.G. (1971). Some statistical models for limited dependent variables with application to demand for durable goods. *Econometrica*, 39(5): 829-844.

[10] Deaton, A. (1987). Estimation of own- and cross-price elasticities from household survey data. *Journal of Econometrics*, 36(1-2): 7-30.

[11] Deaton, A. (1988). Quality, quantity, and spatial variation of price. *American Economic Review*, 78(3): 418-430.

[12] Deaton, A. (1990). Price elasticities from survey data: extensions and Indonesian results. *Journal of Econometrics*, 44(3): 281-309.

[13] Esrey, K. L. Joseph, and S. Glover. (1996). Relationships between dietary intake and coronary heart disease mortality. *Journal of Clinical Epidemiology*, 49(2): 211-216.

[14] Foresight (2007). Tackling obesity: future choices—project report, Government Office for Science: London.

[15] Geweke, J. (2005). *Contemporary Bayesian Econometrics and Statistics*. Wily: Hoboken, New Jersey.

[16] Gostin, L.O. (2007). Law as a tool to facilitate healthier lifestyles. *Journal of the American Medical Association*, 297(1): 87-90.

[17] Gracia, A., and L.M. Albisu. (1998). The demand for meat and fish in Spain: urban and rural areas. *Agricultural Economics*, 19(3): 359-366.

[18] Heckman, J.J. (1979). Sample selection bias as a specification error. *Econometrica*, 47(1): 153-161.

[19] Heien, D., and C.R. Wessells. (1990). Demand systems estimation with microdata - a censored regression approach. *Journal of Business and Economic Statistics*, 8(3): 365-371.

[20] House of Commons Health Committee (HCHC) (2004). Obesity. Third Report of Session 2003-04. House of Commons Report HC 23-I. The Stationary Office: London.

[21] Hu, F., M.J. Stampfer, E. Rimm, G. Colditz, B. Rosner, C.H. Hennekens, and D. Willett. (1997). Dietary fat intake and the risk of coronary heart disease in women. *New England Journal of Medicine*, 337(21): 1491-1499.

[22] Hung, H., K. Joshipura, R. Jiang, F. Hu, D. Hunter, S. Smith-Warner, G. Colditz, B. Rosner, D. Spiegelman, and D. Willett. (2004). Fruit and vegetable intake and risk of major chronic disease. *Journal of the National Cancer Institute*, 96(21): 1577-1584.

[23] Huang, K.S. (1996). Nutrient elasticities in a complete food demand system. *American Journal of Agricultural Economics*, 78(1): 21-29.

[24] Huang, K.S. (1999). Effects of food prices and consumer income on nutrient availability. *Applied Economics*, 31(3): 367-380.

[25] Joshipura, , F. Hu, J. Manson, M. Stampfer, R. Rimm, F. Speizer, G. Colditz, A. Ascherio, B. Rosner, D. Spiegelman, and D. Willett. (2001). The effect of fruit and vegetable intake on risk of coronary heart disease. *Annals of Internal Medicine*, 134(12): 1106-1114.

[26] Marshall, T. (2000). Exploring a fiscal food policy: the case of diet and ischaemic heart disease. *British Medical Journal*, 320(7230): 301-304.

[27] Mytton O., A. Gray, M. Rayner, and H. Rutter (2007). Could targeted food taxes improve health? *Journal of Epidemiology and Community Health*, 61(8): 689-694.

[28] Phaneuf, D.J., C.L. Kling, and J.A. Herriges. (2000). Estimation and welfare calculations in a generalized corner solution model with an application to recreation demand. *Review of Economics and Statistics*, 82(1): 83-92.

[29] Pudney, S. (1989). *Modelling Individual Choice: The Econometrics of Corners, Kinks, and Holes*. Blackwell: Oxford, UK.

[30] Riboli, E., and T. Norat. (2003). Epidemiologic evidence of the protective effect of fruit and vegetables on cancer risk. *American Journal of Clinical Nutrition*, 78(3S): 559S-569S.

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

[32] Stewart, H., and S.T. Yen. (2004). Changing household characteristics and the away-from-home food market: a censored equation system approach. *Food Policy*, 29(6): 643-658.

[33] Tanner, M.A., and W.H. Wong. (1987). The calculation of the posterior distribution by data augmentation (with discussion). *Journal of the American Statistical Association*, 82: 528-550.

[34] Tobin, J. (1958). Estimation of relationships for limited dependent variables. *Econometrica*, 26: 24-36.

[35] Wales, T.J., and A.D. Woodland. (1983). Estimation of consumer demand systems with binding non-negativity constraints. *Journal of Econometrics*, 21(3): 263-285.

[36] Wardle, J., and D. Boniface (2008). Changes in the distributions of body mass index and waist circumference in English adults, 1993/1994 to 2002/2003. *International Journal of Obesity*, 32(3): 527-532.

[37] Yen, S.T. (2005). A multivariate sample-selection model: estimating cigarette and alcohol demands with zero observations. *American Journal of Agricultural Economics*, 87(2): 453-466.

[38] Yen, S.T., and B.H. Lin (2006). A sample selection approach to censored demand systems. *American Journal of Agricultural Economics*, 88(3): 742-749.

[39] Yen, S.T., B.H. Lin, and D.M. (2003). Smallwood. Quasi- and simulated-likelihood approaches to censored demand equations: food consumption by food stamp recipients in the United States. *American Journal of Agricultural Economics*, 85(2): 458-478.

[40] Zellner, A. (1971). *An Introduction to Bayesian Analysis in Econometrics*. John Wiley (reprinted in 1996 as “Wiley Classics” edition): New York, US.

Appendix: Review of Deaton's Approach

Econometric specification

The model consists of two equations where the choice of quantity and quality are a function of expenditures, prices, and household characteristics. The two equations for household i in cluster c are:

$$w_{Gic} = \alpha_G^0 + \beta_G^0 \ln x_{ic} + \gamma_G^0 z_{ic} + \sum_{H=1}^{N} \theta_{GH} \ln p_{Hc} + \left(f_{Gc} + u_{Gic}^0\right) \tag{56}$$

$$\ln v_{Gic} = \alpha_G^1 + \beta_G^1 \ln x_{ic} + \gamma_G^1 z_{ic} + \sum_{H=1}^{N} \psi_{GH} \ln p_{Hc} + u_{Gic}^1, \tag{57}$$

where $i = 1, ..., n$ indicates the total number of households, $H = 1, ...G, ..., N$ indicates the total number of goods, and $c = 1, ..., C$ indicates the total number of clusters.

The budget share equation, equation 56, shows the budget share of good G in household i's budget (w_{Gic}) as a linear function of the logarithm of total expenditure on all goods ($\ln x_{ic}$), a vector of household characteristics (z_{ic}), and the logarithm of unobservable prices for each good in the system (p_{Hc}). There are two components to the error term in the share equation: the cluster-fixed effect, f_{Gc}, is interpreted as the cluster-specific residual in the demand for good G and the standard idiosyncratic error term, u_{Gic}^0, is interpreted as the household-specific residual component. In a typical fixed-effects framework, f_{Gc} may be correlated with the observable explanatory variables, $\ln x_{ic}$ and z_{ic}, but the assumption must be made that f_{Gc} is uncorrelated with p_{Hc}. If this assumption is not made then estimation of price elasticities is not possible, since tastes would vary arbitrarily between clusters. Note there is no i subscript on the price terms, p_{Hc}, since the key assumption is that prices are the same for all households in a particular cluster c.

The unit-value equation, equation 57, shows the logarithm of the unit-value of good G in household i (v_{Gic}) as a function of the same variables in the share equation except omits the cluster-fixed effects. The exclusion of cluster-fixed effects implies unit-value is the sum of the logarithm of quality and the logarithm of price, with price allowed to affect quality choice. In other words, unit-value is a direct indication of price in the absence of quality effects. The exclusion of fixed effects in the unit-value equation is therefore essential to the formulation and relies on spatial variation in unit-value to yield the price information used in the estimation of elasticities. While the budget share for good G is observed for all households in equation 56, the unit value is only observed for households that purchase that particular good at least once. Households with a zero purchase do not generate a corresponding unit value.

The error components, u^0_{Gic} and u^1_{Gic}, are standard idiosyncratic residuals with zero mean and are assumed to be uncorrelated with the explanatory variables, including the cluster-fixed effects. They reflect the typical randomness of econometric models, such as measurement error. The ability of the model to estimate price responses relies on the correlation between u^0_{Gic} and u^1_{Gic}. Unless price is measured perfectly without error (meaning that survey respondents use a perfectly recalled price to either (i) calculate the quantity consumed from price and expenditure or (ii) calculate expenditure from price and quantity), measurement error in unit-value must be correlated with measurement error in the share for good G since the logarithm of unit-value is the difference between the logarithm of expenditure and the logarithm of quantity.

In summary, the key feature is that prices are not observed so it is not possible to estimate the equations directly. Equation 56 can be estimated directly only when the ψ_{GH} matrix is an identity matrix, meaning unit-values and prices shift together. The framework of the model suggests, however, some quality effects exist and unit-values may be measured with error. This implies ψ_{GH} is a diagonal matrix with coefficients different than unity along the diagonal. The affect of or total expenditure and demographic characteristics on consumption is obtained using within-cluster variation in quantities purchased and unit-values. The impact of measurement error is also obtained from the variation in unit-values. Once within-cluster effects are accounted for, estimation of price elasticities is based on the variation of prices between clusters. The formulation implies that since both quantity and quality reflect choices made by consumers, expenditure is not just a function of quantity and price, but also of quality as well. Price and income elasticities of quality must therefore also be accounted for in the derivation of price and income elasticities of quantity. The relationship between the parameters and the elasticities of interest are complicated as a result of the additional quality factor, which is described next.

Elasticity derivation

The total expenditure elasticities of both quantity and quality are simply the quantity demand and quality demand elasticities, respectively, and are obtained from the parameters β_G^0 and β_G^1. Given that unit-value is price multiplied by quantity, if equation 57 is differentiated with respect to $\ln x$ then

$$\frac{\partial \ln v_G}{\partial \ln x} = \beta_G^1, \tag{58}$$

is simply the quality demand elasticity for good G. Equation 56 can also be differentiated with respect to $\ln x$ to yield

$$\frac{\partial \ln w_G}{\partial \ln x} = \frac{\beta_G^0}{w_G}, \tag{59}$$

which is used to obtain the quantity demand elasticity. First, note the logarithm of the budget shares may be written equivalently as the sum of the logarithms of quantity and quality less the logarithm of expenditure

$$\ln w = \ln\left(\frac{x_G}{x}\right) = \ln\left(\frac{v_G q_G}{x}\right) = \ln v_G + \ln q_G - \ln x,$$

where for good G, v_G is the unit-value, x_G is the quantity consumed, and x is the total expenditure on all goods. Second, if the quantity demand elasticity for good G is defined as $\varepsilon_G = {}^{\partial \ln q_G}/_{\partial \ln x}$, then equation 59 may be re-written as

$$\frac{\partial \ln w_G}{\partial \ln x} = \frac{\partial \ln v_G}{\partial \ln x} + \frac{\partial \ln q_G}{\partial \ln x} - 1 = \beta_G^1 + \varepsilon_G - 1. \tag{60}$$

Since equation 59 is equal to 60, solving for ε_G yields the quantity demand elasticity of good G with respect to total expenditure

$$\varepsilon_G = 1 - \beta_G^1 + \frac{\beta_G^0}{w_G}. \tag{61}$$

The price elasticities are also straightforward to derive from the parameters. The derivative of equation 57 with respect to $\ln p_H$ is

$$\frac{\partial \ln v_G}{\partial \ln p_H} = \psi_{GH}, \tag{62}$$

where ψ_{GH} is the matrix of own- and cross-price elasticities of the unit values (i.e., the price effect on the unit-values), which is an identity matrix if price does not effect quality. Equation 57 can also be differentiated with respect to $\ln p_H$ to yield

$$\frac{\partial \ln w_G}{\partial \ln p_H} = \frac{\theta_{GH}}{w_G}. \tag{63}$$

If the matrix of own- and cross-price elasticities is defined as $\varepsilon_{GH} = {}^{\partial \ln q_G}/_{\partial \ln p_H}$, then equation 63 may be re-written as

$$\frac{\partial \ln w_G}{\partial \ln p_H} = \frac{\partial \ln v_G}{\partial \ln p_H} + \frac{\partial \ln q_G}{\partial \ln p_H} - \frac{\partial \ln x}{\partial \ln p_H} = \psi_{GH} + \varepsilon_{GH}, \tag{64}$$

where ${}^{\partial \ln x}/_{\partial \ln p_H} = 0$. Solving for the price elasticities of demand gives

$$\varepsilon_{GH} = -\psi_{GH} + \frac{\theta_{GH}}{w_G}. \tag{65}$$

Clearly, however, not all of the parameters can be estimated since actual prices are not observed. Deaton (1990) identifies a formula that links the effects of prices on quality choice to conventional price and total expenditure elasticities.

In particular, Deaton (1988) shows that if separability is assumed regarding the goods that comprise each heterogeneous commodity then the matrix of price elasticities of the unit values is given by

$$\psi_{GH} = \delta_{GH} + \frac{\beta_G^1 \varepsilon_{GH}}{\varepsilon_G}, \tag{66}$$

where δ_{GH} is the Kronecker delta. Equation 66 implies the quality of good G is only affected by the price of good H when there is a cross-price quantity elasticity ε_{GH}, otherwise ψ_{GH} is simply an identity matrix meaning unit values directly influence prices. If ε_{GH} is present, then the extent of its effect depends on the change in the total quantity of good G, where ${}^{\beta_G^1}/_{\varepsilon_G}$ is the quality elasticity of G with respect to total expenditure on G. Substituting in equation 61 and equation 65 for ε_G and ε_{GH} in equation 66, then

$$\psi_{GH} = \delta_{GH} + \frac{\beta_G^1 \left(\frac{\theta_{GH}}{w_G} - \psi_{GH} \right)}{1 - \beta_G^1 + \frac{\beta_G^0}{w_G}} \tag{67}$$

is the expression that provides a relationship linking the model parameters. In matrix notation, equation 67 is given by

$$\Psi = I + D(\xi)\,\Theta - D(\xi)\,D(w)\,\Psi, \tag{68}$$

where

$$\xi_G = \frac{\beta_G^1}{1 - \beta_G^1 w_G + \beta_G^0}, \tag{69}$$

and I is the $N \times N$ identity matrix and $D(\xi)$ and $D(w)$ are $N \times N$ diagonal matrices with the vectors ξ and w along the diagonals.

Estimation strategy

Estimation proceeds in two stages. In the first stage, equations 56 and 57 are estimated equation by equation using OLS with the cluster means subtracted from the data. The cluster-fixed effects and cluster-invariant prices are removed and yield consistent "within-cluster" estimates of β_G^0, γ_G^0, β_G^1, γ_G^1. Subtracting cluster means from equations 56 and 57 gives

$$(w_{Gic} - w_{G\cdot c}) = \beta_G^0 (\ln x_{ic} - \ln x_{\cdot c}) + \gamma_G^0 (z_{ic} - z_{\cdot c}) + \left(u_{Gic}^0 - u_{G\cdot c}^0\right) \tag{70}$$

$$(\ln v_{Gic} - \ln v_{G\cdot c}) = \beta_G^1 (\ln x_{ic} - \ln x_{\cdot c}) + \gamma_G^1 (z_{ic} - z_{\cdot c}) + \left(u_{Gic}^1 - u_{G\cdot c}^1\right), \tag{71}$$

where the '$\cdot$' subscript represents the means over all households in cluster c. For example, $w_{G\cdot c}$ is the means of household budget share per capita for good G in cluster c. Removing the cluster means from all variables annihilates the price and fixed effects and permits consistent estimation of expenditure and demographic characteristics effects on consumption in both the share and unit-value equations. Equations 70 and 71 represent a set of $2 \times G$ classical multivariate regressions with identical explanatory variables, so using OLS on each equation is efficient. Denote the parameters estimates from the stage 1 regressions as $\tilde{\beta}_G^0$, $\tilde{\gamma}_G^0$, $\tilde{\beta}_G^1$, $\tilde{\gamma}_G^1$ and the estimated residuals as e_{Gic}^0 and e_{Gic}^1. Note that once the parameter estimates are obtained, the expenditure elasticities of quality (β_G^1) and quantity (ε_G) are easily obtained. In addition, the total expenditure elasticity of both quantity and quality together, given by

$\varepsilon_G + \beta_G^1$, can be computed, as can the values of ξ in equation 69.

The second stage of the estimation proceeds with using the first stage parameter estimates to compute the corrected budget shares and unit values, which are then used in the between-cluster estimation of the elasticities. The corrected shares and unit-values are

$$\tilde{y}_{G\cdot c}^0 = w_{G\cdot c} - \tilde{\beta}_G^0 \ln x_{\cdot c} - \tilde{\gamma}_G^0 \cdot z_{\cdot c} \tag{72}$$

$$\tilde{y}_{G\cdot c}^1 = \ln v_{G\cdot c} - \tilde{\beta}_G^1 \ln x_{\cdot c} - \tilde{\gamma}_G^1 \cdot z_{\cdot c}. \tag{73}$$

The population counterparts to equations 56 and 57 are, from 72 and 73, given by

$$y_{G\cdot c}^0 = \tilde{y}_{G\cdot c}^0 + \left(y_{G\cdot c}^0 - \tilde{y}_{G\cdot c}^0\right) = \alpha_G^0 + \sum_{H=1}^{N} \theta_{GH} \ln p_{Hc} + \left(f_{Gc} + u_{G\cdot c}^0\right) \tag{74}$$

$$y_{G\cdot c}^1 = \tilde{y}_{G\cdot c}^1 + \left(y_{G\cdot c}^1 - \tilde{y}_{G\cdot c}^1\right) = \alpha_G^1 + \sum_{H=1}^{N} \psi_{GH} \ln p_{Hc} + u_{G\cdot c}^1. \tag{75}$$

Define the variance-covariance of $y_{G\cdot c}^1$ and the covariance between $y_{G\cdot c}^0$ and $y_{G\cdot c}^1$ as

$$s_{gh} = cov\left(y_{G\cdot c}^1, y_{G\cdot c}^1\right), \tag{76}$$

$$r_{gh} = cov\left(y_{G\cdot c}^0, y_{G\cdot c}^1\right), \tag{77}$$

respectively. Convenient matrix representations of equations s_{GH} and r_{GH} are denoted as S and R. Using these results, the between-cluster estimation of equations 74 and 75 is given by $B = S^{-1}R$.

If there is no measurement error in the cluster averages then $B = S^{-1}R$ is correct, however if there is measurement error present in the recorded expenditures and quantities (as expected) then this formulation is incorrect. In particular, the variance and covariances of prices are overestimated in the presence of measurement error and so the S and R matrices require correction. To obtain a correct estimation of B, the residuals from the stage one regressions, e^0_{Gic} and e^1_{Gic}, are used to obtain consistent estimates of the variances and covariances of the measurement errors u^0_{Gic} and u^1_{Gic} in equation 74 and 75 as follows

$$\sigma^{01}_{GG} = \left(n^+_G - C - k\right)^{-1} \sum_c \sum_i \left(e^1_{Gic}\right)^2, \tag{78}$$

$$\sigma^{10}_{GG} = \left(n^+_G - C - k\right)^{-1} \sum_c \sum_i e^0_{Gic} e^1_{Gic}. \tag{79}$$

Denote the vector n_c as the number of households in each cluster and the vector n^+_{cG} as the number of households in each cluster that purchase good G at least once (i.e., the number of households in each cluster that have observations on both the budget share and the unit-value of good G). The scalar n^+_G is defined as the sum over clusters of n^+_{cG} and represents the total number of households that have positive consumption of good G. Note the summation in equations 78 and 79 is taken only over those households that have an observed unit value. Matrix representation of the residual variances and covariances in equations 78, and 79 are denoted as Ω, and Γ, respectively (which are diagonal matrices of the elements of σ^{01}_{GG} and σ^{10}_{GG}).

The corrected estimation of the B matrix is

$$\tilde{B} = \left(\tilde{S} - \tilde{\Omega}\tilde{T}^{-1}_+\right)^{-1} \left(\tilde{R} - \tilde{\Gamma}\tilde{T}^{-1}_A\right), \tag{80}$$

where the '$\sim$' denotes an estimate and $\tilde{T}^{-1}_+$ and $\tilde{T}^{-1}_A$ are diagonal matrices of the cluster means given by

$$T^{-1}_A = C^{-1} \sum_c \left[D\left(n_c\right)\right]^{-1} \tag{81}$$

$$T^{-1}_+ = C^{-1} \sum_c \left[D\left(n^+_c\right)\right]^{-1}. \tag{82}$$

Note that $\tilde{y}^0_{G\cdot c}$ and $\tilde{y}^1_{G\cdot c}$ are used to provide consistent estimates of the empirical variances and covariances matrices, $\tilde{S}$ and $\tilde{R}$, while $\tilde{\Omega}$ and $\tilde{\Gamma}$ are estimates of Ω and Γ from equations 78 and 79. The value of $\tilde{B}$ converges to B

$$p\lim \tilde{B} = B = \left(\Psi'\right)^{-1} \Theta' \tag{83}$$

as the sample size (i.e., the number of clusters) tends to infinity with cluster sizes remaining constant.

If $\Psi = I$ then $B = \Theta'$ and price effects are directly given by the Θ matrix. Additional information is needed, however, if $\Psi \neq I$, in which case estimates of B do not directly recover Ψ and Θ. This additional information is provided by the expression derived in equation 68 and by the result in equation 83. Calculation of Θ proceeds from

$$\Theta = B' \left[I - D(\xi) B' + D(\xi) D(w)\right]^{-1}. \tag{84}$$

Taking note that the matrix representation of the price elasticities in equation 65 is given by $E = \left[D(w)^{-1}\Theta - \Psi\right]$, substituting gives

$$E = \left[D(w)^{-1} B' - I\right] \left[I - D(\xi) B' + D(\xi) D(w)\right]^{-1}. \tag{85}$$

Estimates of both Θ and E are calculated using estimates from the first and second stages and by using the sample mean budget shares in the w vector.

In addition to complicated matrix multiplication, the main problem of applying Deaton's approach to estimating demand elasticities is that there is no guarantee of obtaining accurate estimates. Given that the residual covariance matrices S, R, Ω, and Γ are influenced by a variety of unexplained factors, price variation being just one possible factor, there is considerable imprecision to the Deaton approach. Since the estimated elasticities are essentially obtained through a between-cluster regression, the since the sample used here does not have many clusters, the application of the Deaton approach to the 2003-2004 EFS data yielded elasticity estimates deemed unsatisfactory.

Table 1: Major food groups

Main Food Groups	Sub-Food Groups	Mean Consumption	Mean Unit Value	Mean Budget Share
Dairy & Eggs	Cheeses	0.63	0.51	0.03
	Eggs	0.01	11.71	0.01
	Milk & cream	8.59	0.06	0.06
	Other dairy	2.10	0.21	0.04
Meat & Fish	Beef	0.80	0.48	0.03
	Lamb	0.24	0.55	0.01
	Pork	1.15	0.55	0.05
	Poultry	1.15	0.45	0.04
	Fish	0.66	0.57	0.03
	Other meats	1.43	0.46	0.06
Staples & Starches	Breads	3.71	0.11	0.04
	Breakfast cereals	0.72	0.29	0.02
	Rice & pasta	0.69	0.18	0.01
	Potatoes	3.17	0.09	0.02
	Other starches	0.65	0.55	0.03
Fruit & Vegetables	Fresh	6.96	0.17	0.11
	Frozen	0.36	0.15	0.01
	Tinned & processed	0.75	0.16	0.01
	One-a-day only	2.17	0.13	0.02
	Other fruit & veg	0.29	0.44	0.01
Fats & Sugars	All fats	1.05	0.29	0.02
	Biscuit, cakes, pastry	1.64	0.36	0.05
	Chips and Crisps	1.03	0.40	0.03
	Candies & other sweets	1.34	0.46	0.05
Beverages	Alcohol	3.67	0.41	0.10
	Soft drinks	9.46	0.06	0.04
	Tea & coffee	0.26	0.83	0.02
	Water	1.11	0.04	0.00
Hot Takeaway		0.58	1.01	0.05

Table 2: Nutritive content of food

	Total Energy kcal	Saturated Fat g	Animal Protein g	Vegetable Protein g	Carbs g	Calcium mg	Iron mg
Cheeses	3.255	0.166	0.196	0.000	0.031	5.280	0.002
Eggs	76.238	1.602	6.357	0.000	0.000	28.990	0.966
Milk & cream	0.575	0.018	0.034	0.000	0.049	1.173	0.001
Other dairy	1.018	0.027	0.030	0.001	0.135	0.969	0.001
Beef	2.116	0.063	0.197	0.001	0.006	0.099	0.017
Lamb	1.848	0.063	0.154	0.000	0.000	0.081	0.013
Pork	2.124	0.055	0.164	0.003	0.024	0.332	0.007
Poultry	1.235	0.019	0.158	0.000	0.001	0.051	0.005
Fish	1.288	0.014	0.147	0.007	0.037	0.670	0.009
Other meats	2.182	0.051	0.092	0.032	0.125	0.384	0.014
Breads	2.350	0.005	0.000	0.086	0.485	1.526	0.018
Breakfast cereals	3.508	0.008	0.001	0.080	0.770	0.881	0.109
Rice & pasta	2.914	0.003	0.001	0.072	0.666	0.183	0.010
Potatoes	0.475	0.001	0.000	0.012	0.100	0.057	0.003
Other starches	3.257	0.048	0.029	0.073	0.443	1.583	0.017
Fresh	0.317	0.001	0.000	0.008	0.067	0.159	0.003
Frozen	0.535	0.002	0.000	0.036	0.082	0.312	0.009
Tinned & processed	0.653	0.001	0.000	0.018	0.148	0.201	0.008
One-a-day only	0.703	0.004	0.000	0.024	0.111	0.218	0.006
Other fruit & veg	1.731	0.023	0.002	0.032	0.185	0.487	0.008
All fats	6.367	0.192	0.007	0.004	0.032	0.153	0.002
Biscuit, cakes, pastry	4.063	0.085	0.010	0.048	0.595	0.846	0.017
Chips and Crisps	2.710	0.053	0.000	0.038	0.346	0.154	0.011
Candies & other sweets	3.926	0.048	0.024	0.003	0.811	0.574	0.008
Alcohol	0.515	0.000	0.000	0.002	0.012	0.065	0.002
Soft drinks	0.242	0.000	0.000	0.000	0.064	0.037	0.000
Tea & coffee	0.730	0.005	0.003	0.052	0.114	0.804	0.024
Water	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Hot Takeaway	1.937	0.032	0.079	0.044	0.168	0.580	0.010

Table 3: Nutritive share of food

	Total Energy kcal	Saturated Fat g	Animal Protein g	Vegetable Protein g	Carbs g	Calcium mg	Iron mg
Cheeses	0.029	0.089	0.082	0.000	0.002	0.089	0.003
Eggs	0.008	0.010	0.031	0.000	0.000	0.006	0.013
Milk & cream	0.069	0.132	0.192	0.000	0.047	0.268	0.007
Other dairy	0.030	0.047	0.042	0.002	0.032	0.054	0.005
Beef	0.024	0.042	0.104	0.001	0.001	0.002	0.023
Lamb	0.006	0.013	0.025	0.000	0.000	0.001	0.006
Pork	0.034	0.054	0.125	0.002	0.003	0.010	0.014
Poultry	0.020	0.018	0.121	0.000	0.000	0.002	0.009
Fish	0.012	0.008	0.064	0.003	0.003	0.012	0.010
Other meats	0.044	0.061	0.087	0.034	0.020	0.015	0.034
Breads	0.122	0.014	0.001	0.236	0.201	0.151	0.118
Breakfast cereals	0.035	0.005	0.000	0.043	0.062	0.017	0.137
Rice & pasta	0.028	0.002	0.000	0.037	0.051	0.003	0.012
Potatoes	0.002	0.000	0.000	0.002	0.003	0.000	0.001
Other starches	0.029	0.026	0.012	0.035	0.032	0.027	0.019
Fresh	0.031	0.004	0.000	0.043	0.052	0.030	0.038
Frozen	0.003	0.000	0.000	0.010	0.003	0.003	0.006
Tinned & processed	0.007	0.000	0.000	0.010	0.012	0.004	0.011
One-a-day only	0.021	0.008	0.000	0.038	0.027	0.013	0.024
Other fruit & veg	0.007	0.006	0.000	0.007	0.006	0.004	0.004
All fats	0.093	0.170	0.005	0.003	0.004	0.004	0.003
Biscuit, cakes, pastry	0.093	0.118	0.011	0.058	0.109	0.037	0.048
Chips and Crisps	0.039	0.046	0.000	0.029	0.040	0.004	0.019
Candies & other sweets	0.073	0.054	0.021	0.003	0.121	0.020	0.018
Alcohol	0.004	0.000	0.000	0.001	0.001	0.001	0.003
Soft drinks	0.012	0.000	0.000	0.000	0.026	0.004	0.000
Tea & coffee	0.096	0.044	0.019	0.366	0.121	0.203	0.398
Water	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Hot Takeaway	0.030	0.030	0.058	0.036	0.021	0.017	0.019

Table 4: Fiscal food policy

Index	Sub-food Group	Tax/Subsidy
1	Cheeses	15.00%
2	Eggs	3.20%
3	Milk & cream	1.82%
4	Other dairy	2.69%
5	Beef	6.28%
6	Lamb	6.30%
7	Pork	5.54%
8	Poultry	1.86%
9	Fish	1.36%
10	Other meats	5.08%
11	Breads	0.46%
12	Breakfast cereals	0.79%
13	Rice & pasta	0.29%
14	Potatoes	0.12%
15	Other starches	4.76%
16	Fresh	-26.76%
17	Frozen	-26.76%
18	Tinned & processed	-26.76%
19	One-a-day only	0.42%
20	Other fruit & veg	2.26%
21	All fats	15.00%
22	Biscuit, cakes, pastry	8.52%
23	Chips and Crisps	5.26%
24	Candies & other sweets	4.76%
25	Alcohol	0.01%
26	Soft drinks	0.00%
27	Tea & coffee	0.55%
28	Water	0.00%
29	Hot Takeaway	3.15%

Table 5: Demand elasticities

Index	Sub-food Group	Own-price	Stand. Dev.	Expenditure	Stand. Dev.
1	Cheeses	-0.655	0.030	0.878	0.014
2	Eggs	-0.747	0.030	0.502	0.023
3	Milk & cream	-0.601	0.032	0.965	0.012
4	Other dairy	-0.981	0.037	1.352	0.018
5	Beef	-0.853	0.041	0.829	0.019
6	Lamb	-0.910	0.041	0.834	0.023
7	Pork	-0.842	0.037	0.851	0.019
8	Poultry	-0.948	0.021	0.830	0.016
9	Fish	-0.688	0.039	0.799	0.019
10	Other meats	-1.636	0.108	1.654	0.034
11	Breads	-0.717	0.027	0.876	0.013
12	Breakfast cereals	-0.729	0.030	0.835	0.014
13	Rice & pasta	-0.781	0.025	0.806	0.020
14	Potatoes	-0.946	0.028	0.771	0.025
15	Other starches	-1.267	0.055	1.517	0.022
16	Fresh	-0.985	0.022	1.103	0.008
17	Frozen	-1.105	0.044	0.642	0.023
18	Tinned & processed	-0.908	0.039	0.518	0.021
19	One-a-day only	-0.805	0.031	0.667	0.017
20	Other fruit & veg	-1.213	0.053	1.553	0.033
21	All fats	-0.607	0.029	0.641	0.019
22	Biscuit, cakes, pastry	-0.751	0.025	1.007	0.016
23	Chips and Crisps	-0.890	0.033	0.817	0.018
24	Candies & other sweets	-0.983	0.041	1.379	0.020
25	Alcohol	-1.000	0.022	1.091	0.008
26	Soft drinks	-0.930	0.022	0.856	0.011
27	Tea & coffee	-0.929	0.025	0.626	0.010
28	Water	-1.816	0.067	1.774	0.029
29	Hot Takeaway	-1.097	0.136	1.358	0.134

Table 6: Nutrient elasticities for dairy and eggs group

Nutrient	Cheese	Eggs	Milk & Cream	Other Dairy	Dairy Expend
Vegetable Protein	0.000	0.000	-0.001	-0.002	0.002
Animal Protein	-0.090	-0.036	-0.147	-0.053	0.330
Fat	-0.054	-0.017	-0.073	-0.034	0.179
Saturates	-0.086	-0.017	-0.115	-0.056	0.275
Mono-unsaturates	-0.039	-0.016	-0.054	-0.024	0.134
Poly-unsaturates	-0.012	-0.011	-0.017	-0.008	0.049
Carbohydrate	-0.013	-0.003	-0.039	-0.036	0.090
Energy - Kcal	-0.034	-0.011	-0.057	-0.034	0.136
Calcium	-0.112	-0.022	-0.199	-0.080	0.413
Iron	-0.002	-0.010	-0.007	-0.002	0.022
Retinol	-0.080	-0.036	-0.104	-0.021	0.248
Carotene	-0.014	-0.002	-0.021	-0.011	0.048
Retinol equivalent	-0.058	-0.025	-0.077	-0.018	0.182
Thiamin	-0.014	-0.007	-0.037	-0.033	0.090
Riboflavin	-0.040	-0.020	-0.104	-0.043	0.208
Niacin Equivalent	-0.018	-0.008	-0.028	-0.011	0.066
Vitamin C	-0.013	-0.004	-0.043	-0.013	0.073
Vitamin D	-0.014	-0.049	-0.042	0.000	0.113
Folate	-0.011	-0.009	-0.021	-0.009	0.052
Sodium	-0.038	-0.008	-0.040	-0.016	0.102
Starch	-0.001	0.000	-0.003	-0.008	0.011
Glucose	-0.007	-0.001	-0.018	-0.049	0.072
Fructose	-0.005	-0.001	-0.011	-0.032	0.046
Sucrose	-0.008	-0.001	-0.019	-0.052	0.076
Maltose	-0.002	0.000	-0.005	-0.012	0.019
Lactose	-0.147	-0.043	-0.455	-0.196	0.837
Other sugars	-0.015	-0.004	-0.046	-0.060	0.121
Total sugars	-0.026	-0.006	-0.075	-0.066	0.170
Non-milk extr sugars	-0.008	-0.001	-0.020	-0.051	0.076
Potassium	-0.011	-0.004	-0.032	-0.016	0.062
Magnesium	-0.012	-0.004	-0.028	-0.014	0.058
Copper	-0.010	-0.002	-0.005	-0.001	0.019
Zinc	-0.042	-0.014	-0.063	-0.021	0.141
Vitamin B6	-0.016	-0.008	-0.040	-0.011	0.076
Vitamin B12	-0.099	-0.056	-0.234	-0.056	0.452
Phosphorus	-0.058	-0.019	-0.105	-0.043	0.227
Biotin	-0.010	-0.016	-0.028	-0.008	0.064
Pantothenic acid	-0.030	-0.022	-0.091	-0.033	0.178
Vitamin E	-0.009	-0.010	-0.020	-0.017	0.057
Cholesterol	-0.039	-0.142	-0.074	0.020	0.257

Table 7: Nutrient elasticities for meat and fish group

Nutrient	Beef	Lamb	Pork	Poultry	Fish	Other Meats	Meat/Fish Expend
Vegetable Protein	-0.002	-0.001	-0.007	-0.002	-0.005	-0.055	0.061
Animal Protein	-0.098	-0.025	-0.120	-0.121	-0.064	-0.071	0.507
Fat	-0.037	-0.012	-0.059	-0.029	-0.020	-0.085	0.234
Saturates	-0.040	-0.013	-0.054	-0.021	-0.016	-0.079	0.214
Mono-unsaturates	-0.046	-0.013	-0.070	-0.037	-0.023	-0.100	0.277
Poly-unsaturates	-0.013	-0.005	-0.052	-0.032	-0.023	-0.064	0.183
Carbohydrate	-0.001	-0.001	-0.005	-0.001	-0.004	-0.032	0.038
Energy - Kcal	-0.023	-0.007	-0.035	-0.022	-0.015	-0.056	0.152
Calcium	-0.003	-0.002	-0.011	-0.003	-0.010	-0.020	0.046
Iron	-0.022	-0.007	-0.017	-0.011	-0.012	-0.046	0.109
Retinol	-0.030	-0.081	-0.050	-0.008	-0.025	-0.155	0.328
Carotene	-0.002	-0.001	-0.004	-0.002	-0.004	-0.052	0.055
Retinol equivalent	-0.021	-0.055	-0.035	-0.006	-0.018	-0.121	0.238
Thiamin	-0.006	-0.003	-0.064	-0.014	-0.011	-0.066	0.157
Riboflavin	-0.012	-0.006	-0.015	-0.014	-0.008	-0.022	0.075
Niacin Equivalent	-0.033	-0.009	-0.044	-0.053	-0.024	-0.038	0.202
Vitamin C	-0.003	-0.001	-0.015	-0.001	-0.003	-0.031	0.049
Vitamin D	-0.045	-0.022	-0.068	-0.036	-0.114	-0.032	0.328
Folate	-0.006	-0.002	-0.004	-0.005	-0.004	-0.012	0.032
Sodium	-0.020	-0.004	-0.107	-0.020	-0.029	-0.112	0.280
Starch	-0.002	-0.001	-0.008	-0.002	-0.007	-0.056	0.066
Glucose	-0.001	0.000	-0.008	-0.001	-0.001	-0.016	0.025
Fructose	0.000	0.000	-0.001	-0.001	-0.001	-0.012	0.013
Sucrose	0.000	0.000	0.000	0.000	0.000	-0.004	0.005
Maltose	-0.001	0.000	-0.010	-0.001	-0.001	-0.013	0.024
Lactose	0.000	0.000	-0.001	0.000	-0.001	-0.007	0.008
Other sugars	0.000	0.000	0.000	-0.002	0.000	-0.005	0.006
Total sugars	0.000	0.000	-0.002	0.000	-0.001	-0.008	0.010
Non-milk extr sugars	0.000	0.000	0.000	0.000	0.000	-0.001	0.002
Potassium	-0.008	-0.002	-0.010	-0.010	-0.006	-0.012	0.048
Magnesium	-0.006	-0.002	-0.009	-0.009	-0.007	-0.014	0.045
Copper	-0.005	-0.009	-0.008	-0.004	-0.006	-0.026	0.055
Zinc	-0.061	-0.014	-0.037	-0.024	-0.017	-0.042	0.196
Vitamin B6	-0.034	-0.007	-0.049	-0.040	-0.019	-0.033	0.182
Vitamin B12	-0.089	-0.047	-0.048	-0.017	-0.094	-0.079	0.375
Phosphorus	-0.024	-0.008	-0.036	-0.029	-0.021	-0.039	0.156
Biotin	-0.003	-0.002	-0.008	-0.005	-0.005	-0.014	0.035
Vitamin	-0.006	-0.003	-0.011	-0.004	-0.015	-0.027	0.064
Cholesterol	-0.059	-0.023	-0.086	-0.100	-0.048	-0.095	0.407

Table 8: Nutrient elasticities for staples and starches group

Nutrient	Breads	Breakfast Cereals	Rice & Pasta	Potatoes	Other Staples	Staples Expend
Vegetable Protein	-0.185	-0.057	-0.037	-0.002	-0.035	0.327
Animal Protein	-0.004	-0.002	-0.001	0.000	-0.015	0.020
Fat	-0.029	-0.011	-0.005	-0.001	-0.035	0.077
Saturates	-0.019	-0.007	-0.003	-0.001	-0.032	0.058
Mono-unsaturates	-0.021	-0.009	-0.004	-0.001	-0.035	0.065
Poly-unsaturates	-0.048	-0.019	-0.009	-0.002	-0.045	0.120
Carbohydrate	-0.162	-0.068	-0.048	-0.003	-0.027	0.320
Energy - Kcal	-0.101	-0.040	-0.027	-0.002	-0.029	0.204
Calcium	-0.118	-0.028	-0.008	0.000	-0.033	0.191
Iron	-0.106	-0.112	-0.016	-0.002	-0.007	0.257
Retinol	-0.006	-0.003	-0.001	0.000	-0.014	0.022
Carotene	-0.004	-0.005	-0.003	0.000	-0.013	0.022
Retinol equivalent	-0.005	-0.003	-0.001	0.000	-0.013	0.022
Thiamin	-0.145	-0.146	-0.019	-0.004	-0.010	0.340
Riboflavin	-0.024	-0.050	-0.003	-0.001	-0.001	0.083
Niacin Equivalent	-0.044	-0.039	-0.008	-0.001	-0.008	0.103
Folate	-0.052	-0.063	-0.009	-0.003	0.002	0.132
Sodium	-0.158	-0.049	-0.015	-0.001	-0.061	0.285
Starch	-0.300	-0.106	-0.090	-0.006	-0.050	0.574
Glucose	-0.013	-0.024	-0.004	-0.001	-0.005	0.048
Fructose	-0.019	-0.027	-0.005	-0.001	-0.005	0.060
Sucrose	-0.006	-0.030	-0.002	-0.001	0.001	0.041
Maltose	-0.194	-0.033	-0.037	0.001	-0.026	0.302
Lactose	-0.002	-0.004	0.000	0.000	-0.004	0.009
Other sugars	-0.015	-0.002	-0.001	0.000	-0.009	0.027
Total sugars	-0.024	-0.029	-0.006	-0.001	-0.003	0.065
Non-milk extr sugars	-0.005	-0.025	-0.002	0.000	0.001	0.033
Fibre:Southgate	-0.218	-0.103	-0.038	-0.004	-0.040	0.418
Potassium	-0.017	-0.008	-0.004	-0.002	-0.005	0.037
Magnesium	-0.041	-0.020	-0.009	-0.001	-0.009	0.082
Copper	-0.040	-0.017	-0.011	-0.001	-0.008	0.079
Zinc	-0.066	-0.026	-0.016	-0.001	-0.017	0.130
Vitamin B6	-0.047	-0.101	-0.016	-0.008	0.006	0.178
Vitamin B12	-0.007	-0.026	-0.002	-0.001	-0.005	0.041
Phosphorus	-0.065	-0.029	-0.015	-0.001	-0.018	0.131
Biotin	-0.013	-0.008	-0.003	0.000	-0.005	0.030
Pantothenic acid	-0.038	-0.030	-0.010	-0.002	-0.011	0.094
Vitamin E	-0.017	-0.014	-0.007	-0.002	-0.029	0.065
Cholesterol	-0.005	-0.002	-0.001	0.000	-0.015	0.020

Table 9: Nutrient elasticities for fruits and vegetables group

Nutrient	Fresh	Frozen	Tinned & Processed	One-a-Day Only	Other Fruit/Veg	Fruit/Veg Expend
Vegetable Protein	-0.036	-0.011	-0.010	-0.033	-0.001	0.095
Fat	-0.012	-0.001	0.000	-0.013	-0.010	0.036
Saturates	-0.007	0.000	0.000	-0.006	-0.006	0.019
Mono-unsaturates	-0.010	0.000	0.000	-0.015	-0.007	0.033
Poly-unsaturates	-0.028	-0.002	-0.001	-0.025	-0.027	0.082
Carbohydrate	-0.047	-0.004	-0.012	-0.024	-0.003	0.093
Energy - Kcal	-0.030	-0.003	-0.007	-0.019	-0.005	0.064
Calcium	-0.028	-0.003	-0.004	-0.012	-0.003	0.051
Iron	-0.032	-0.006	-0.011	-0.021	0.000	0.073
Retinol	-0.004	0.000	0.000	0.000	-0.007	0.008
Carotene	-0.590	-0.081	-0.053	-0.041	-0.062	0.818
Retinol equivalent	-0.191	-0.026	-0.017	-0.013	-0.024	0.267
Thiamin	-0.054	-0.011	-0.007	-0.026	-0.003	0.104
Riboflavin	-0.014	-0.002	-0.002	-0.006	0.000	0.025
Niacin Equivalent	-0.017	-0.003	-0.004	-0.011	0.000	0.037
Vitamin C	-0.345	-0.045	-0.033	-0.251	0.006	0.690
Vitamin D	-0.004	0.000	0.000	0.000	-0.008	0.010
Folate	-0.062	-0.011	-0.005	-0.024	-0.002	0.105
Sodium	-0.009	-0.001	-0.007	-0.026	-0.012	0.058
Starch	-0.007	-0.004	-0.004	-0.011	-0.007	0.034
Glucose	-0.205	-0.005	-0.073	-0.092	0.008	0.381
Fructose	-0.296	-0.005	-0.080	-0.121	0.005	0.511
Sucrose	-0.059	-0.003	-0.007	-0.027	-0.001	0.100
Maltose	0.001	0.000	-0.005	0.000	0.001	0.004
Lactose	-0.001	0.000	0.000	0.000	-0.003	0.003
Other sugars	-0.057	-0.022	-0.005	-0.005	-0.002	0.092
Total sugars	-0.088	-0.004	-0.021	-0.037	0.000	0.154
Non-milk extr sugars	0.010	-0.002	-0.014	-0.046	0.011	0.049
Fibre:Southgate	-0.165	-0.033	-0.034	-0.066	0.000	0.305
Potassium	-0.040	-0.003	-0.007	-0.015	-0.001	0.067
Magnesium	-0.023	-0.004	-0.005	-0.017	0.001	0.050
Copper	-0.026	-0.001	-0.008	-0.008	0.000	0.044
Zinc	-0.019	-0.005	-0.004	-0.012	-0.001	0.041
Vitamin B6	-0.080	-0.005	-0.009	-0.023	-0.006	0.124
Vitamin B12	-0.001	0.000	0.000	0.000	-0.002	0.002
Phosphorus	-0.024	-0.005	-0.005	-0.016	-0.001	0.052
Biotin	-0.014	-0.001	-0.002	-0.017	0.002	0.034
Pantothenic acid	-0.041	-0.003	-0.004	-0.011	-0.002	0.061
Vitamin E	-0.075	-0.004	-0.012	-0.022	-0.027	0.139
Cholesterol	-0.003	0.000	0.000	0.000	-0.005	0.006

Table 10: Nutrient elasticities for fats and sugars group

Nutrient	All Fats	Biscuits, Cakes	Chips & Crisps	Candies & Other	Fat/Sugars Expend
Vegetable Protein	-0.009	-0.044	-0.028	-0.008	0.089
Fat	-0.165	-0.086	-0.054	-0.030	0.351
Saturates	-0.122	-0.104	-0.050	-0.053	0.339
Mono-unsaturates	-0.172	-0.086	-0.061	-0.027	0.363
Poly-unsaturates	-0.270	-0.048	-0.054	0.015	0.388
Carbohydrate	-0.028	-0.118	-0.044	-0.130	0.312
Energy - Kcal	-0.075	-0.092	-0.042	-0.074	0.286
Calcium	-0.008	-0.034	-0.006	-0.025	0.072
Iron	-0.009	-0.041	-0.019	-0.022	0.091
Retinol	-0.150	-0.018	-0.006	0.007	0.185
Carotene	-0.032	-0.004	-0.002	-0.001	0.042
Retinol equivalent	-0.116	-0.013	-0.005	0.005	0.142
Thiamin	-0.005	-0.023	-0.019	-0.006	0.054
Riboflavin	-0.003	-0.012	-0.004	-0.011	0.029
Niacin Equivalent	-0.004	-0.011	-0.014	-0.004	0.033
Vitamin C	-0.004	-0.002	-0.036	-0.001	0.044
Vitamin D	-0.172	-0.015	-0.007	0.016	0.197
Sodium	-0.041	-0.046	-0.032	-0.010	0.134
Starch	-0.015	-0.084	-0.073	-0.012	0.187
Glucose	-0.032	-0.111	-0.012	-0.164	0.308
Fructose	-0.023	-0.079	-0.008	-0.097	0.200
Sucrose	-0.061	-0.230	-0.022	-0.380	0.665
Maltose	-0.014	-0.052	-0.005	-0.094	0.157
Lactose	-0.012	-0.036	-0.003	-0.046	0.094
Other sugars	-0.023	-0.058	-0.008	-0.180	0.255
Total sugars	-0.041	-0.151	-0.014	-0.246	0.435
Non-milk extr sugars	-0.056	-0.206	-0.018	-0.349	0.605
Fibre:Southgate	-0.012	-0.049	-0.071	-0.008	0.143
Potassium	-0.004	-0.008	-0.024	-0.004	0.040
Magnesium	-0.005	-0.015	-0.014	-0.010	0.044
Copper	-0.007	-0.022	-0.016	-0.016	0.060
Zinc	-0.006	-0.021	-0.012	-0.012	0.052
Vitamin B6	-0.006	-0.007	-0.055	0.004	0.066
Vitamin B12	-0.006	-0.007	-0.001	-0.005	0.018
Phosphorus	-0.008	-0.029	-0.018	-0.016	0.072
Biotin	-0.004	-0.009	-0.002	-0.005	0.020
Pantothenic acid	-0.005	-0.013	-0.012	-0.008	0.037
Vitamin E	-0.294	-0.045	-0.107	0.015	0.466
Cholesterol	-0.059	-0.059	-0.005	-0.016	0.143

Table 11: Nutrient elasticities for drinks group

Nutrient	Alcohol	Soft Drinks	Tea & Coffee	Water	Drinks Expend
Vegetable Protein	0.060	0.017	-0.340	0.121	0.231
Animal Protein	0.003	0.001	-0.017	0.006	0.012
Fat	0.005	0.001	-0.027	0.010	0.018
Saturates	0.007	0.002	-0.041	0.015	0.028
Mono-unsaturates	0.004	0.001	-0.023	0.008	0.015
Poly-unsaturates	0.001	0.000	-0.005	0.002	0.004
Carbohydrate	0.022	-0.019	-0.113	0.043	0.099
Energy - Kcal	0.013	-0.007	-0.090	0.033	0.076
Calcium	0.033	0.006	-0.189	0.068	0.131
Iron	0.064	0.019	-0.369	0.132	0.252
Retinol	0.024	0.007	-0.134	0.048	0.090
Carotene	0.002	-0.018	-0.002	0.002	0.017
Retinol equivalent	0.017	-0.001	-0.090	0.033	0.066
Thiamin	0.035	0.010	-0.193	0.069	0.130
Riboflavin	0.093	0.026	-0.520	0.186	0.352
Niacin Equivalent	0.084	0.021	-0.469	0.168	0.321
Vitamin C	0.006	-0.047	-0.005	0.007	0.046
Vitamin D	0.018	0.005	-0.103	0.037	0.069
Folate	0.103	0.028	-0.575	0.205	0.390
Sodium	0.015	0.002	-0.083	0.030	0.059
Starch	0.008	0.002	-0.046	0.016	0.031
Glucose	0.019	-0.126	-0.049	0.030	0.151
Fructose	0.014	-0.140	-0.012	0.018	0.136
Sucrose	0.039	-0.026	-0.203	0.076	0.170
Maltose	0.075	0.013	-0.447	0.160	0.317
Lactose	0.013	0.004	-0.073	0.026	0.049
Other sugars	0.094	0.019	-0.525	0.188	0.363
Total sugars	0.036	-0.040	-0.182	0.069	0.168
Non-milk extr sugars	0.050	-0.059	-0.250	0.096	0.236
Alcohol	-1.000	-0.037	-0.079	-0.034	1.091
Potassium	0.120	0.034	-0.676	0.241	0.458
Magnesium	0.114	0.031	-0.645	0.230	0.440
Copper	0.120	0.035	-0.675	0.241	0.456
Zinc	0.066	0.019	-0.368	0.131	0.248
Vitamin B6	0.047	0.000	-0.269	0.097	0.197
Vitamin B12	0.006	-0.006	-0.031	0.012	0.028
Phosphorus	0.051	0.012	-0.291	0.104	0.201
Biotin	0.131	0.036	-0.738	0.264	0.502
Pantothenic acid	0.056	0.016	-0.418	0.148	0.307
Cholesterol	0.002	0.000	-0.009	0.003	0.006

Table 12: Nutrient elasticities for hot takeaway group

Nutrient	Hot Takeaway	HT Expend
Vegetable Protein	-0.040	0.049
Animal Protein	-0.064	0.079
Fat	-0.038	0.046
Saturates	-0.032	0.040
Mono-unsaturates	-0.043	0.054
Poly-unsaturates	-0.039	0.048
Carbohydrate	-0.023	0.028
Energy - Kcal	-0.033	0.041
Calcium	-0.019	0.023
Iron	-0.020	0.025
Retinol	-0.009	0.011
Carotene	-0.036	0.044
Retinol equivalent	-0.018	0.022
Thiamin	-0.023	0.029
Riboflavin	-0.009	0.011
Niacin Equivalent	-0.032	0.039
Vitamin C	-0.018	0.022
Vitamin D	-0.029	0.036
Folate	-0.010	0.012
Sodium	-0.041	0.051
Starch	-0.041	0.050
Glucose	-0.011	0.014
Fructose	-0.008	0.010
Sucrose	-0.001	0.002
Maltose	-0.010	0.012
Lactose	-0.005	0.006
Other sugars	-0.014	0.017
Total sugars	-0.005	0.006
Fibre:Southgate	-0.031	0.038
Potassium	-0.009	0.012
Magnesium	-0.013	0.016
Copper	-0.013	0.016
Zinc	-0.030	0.037
Vitamin B6	-0.025	0.031
Vitamin B12	-0.037	0.046
Phosphorus	-0.032	0.039
Pantothenic acid	-0.024	0.030
Vitamin E	-0.032	0.039
Cholesterol	-0.055	0.068