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Taxing fat versus behavioural interventions: Multiple discrete–continuous extreme value (MDCEV) models and the PCSHOP randomized trial of shopping behaviour

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ABSTRACT

Understanding food purchasing behaviours is complex because people make both choices among goods and volumes of those goods that they choose. We use the novel Multiple Discrete-Continuous Extreme Value (MDCEV) model, capable of handling both aspects of behaviour, on real-world food shopping behaviour data from a clinical trial. We compared the impact of providing general dietary advice, general dietary advice plus personalised shopping advice, or taxation, and combinations thereof, on the amount of saturated fat in consumers' shopping baskets, using simulation. We used supermarket loyalty card data from a randomized controlled trial of 111 adults with raised cholesterol in Oxfordshire (UK). A Danish fat tax simulation alone is less effective than the tax in combination with dietary and shopping advice. These data illustrate the potential of MDCEV models for these behaviours and, by extension, informing food policies.

1. Introduction

Poor diet is a major contributor to cardiovascular disease (CVD), the leading cause of death worldwide (World Health Organization, 2020). Population dietary recommendations and individual clinical guidelines for CVD prevention encourage saturated fat (SFA) intake < 10 % of total energy, or < 7 % for patients with dyslipidaemia (SACN, 2021; Mach et al., 2020). National surveys show that intake of SFA in the UK ranges from 12.3 to 14.1 % energy among adults and is relatively unchanged in recent years (Public Health England, 2020; Pot et al., 2012). A Cochrane *meta*-analysis of randomised controlled trials (RCTs) aiming to decrease SFA intake has shown significant reductions in LDL cholesterol can lead to a 17 % reduction in CVD events (Hooper et al., 2020).

One of the main approaches to reducing SFA intake is behavioural interventions. The Primary Care Shopping Intervention for Cardiovascular Disease Prevention (PCSHOP) randomised controlled trial tested a novel and scalable behavioural intervention to achieve reductions in SFA intakes among patients with raised LDL-cholesterol (Piernas et al., 2020). The intervention delivered general dietary advice from a nurse in primary care alone and in combination with personalised advice and feedback on food choices (i.e. healthier swaps), and resulted in a modest but non-significant reduction in SFA intake compared to no intervention (Piernas et al., 2020). The results from the PCSHOP study agree with other low-cost scalable interventions in primary care with potential to prevent non-communicable disease risk (Aveyard et al., 2016; Payne Riches et al., 2021).

Another common approach to reducing SFA is via pricing of goods. Meta-analytic evidence supports the economic theory that prices can impact food choices (Green et al., 2013; Andreyeva et al., 2010; Mizdrak et al., 2015; Niebylski et al., 2015). Taxes that are targeted either at food

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groups (Teng et al., 2019;Cornelsen et al., 2015) or at nutrients, e.g. salt or sugar (Dodd et al., 2020; Eyles et al., 2012), have been found to help reduce those purchases, but substitution to other products may be more or less healthy. Regarding saturated fat (SFA), the Danish tax on meat, dairy, and spreads (where the saturated fat level exceeded 2.3 g/100 g) reduced intake of saturated fat by around 4 % (Smed et al., 2016). A *meta*-analysis found a 0.02 % reduction in energy intake from SFA for a 1 % price increases through flat-rate taxes (Eyles et al., 2012). Though recent evidence indicates that price interventions are more impactful than labelling and in-store promotions (Slapø et al., 2021) or educational interventions within the supermarket context (Hartmann-Boyce et al., 2018), how taxes compare or interact with behavioural interventions has not been explored before.

The Multiple Discrete-Continuous Extreme Value (MDCEV) choice model is a structural demand model that has newly been applied in food research and shows promise for understanding people's behaviours (Bhat, 2008; Lu et al., 2017). This approach can accommodate behavioural interventions and price variation if data are available, though has not been used as yet for this purpose. In the context of food behaviours, MDCEV models have not been used with real-world behavioural data.

The present study used data from the PCSHOP randomised controlled trial to perform a comparative analysis of behavioural interventions and taxation as tools for CVD prevention. We used an MDCEV to model trial participants' shopping behaviours and predicted how behavioural interventions and increased taxes impacted the amount of saturated fat in weekly shopping baskets. This allowed us to analyse whether the behavioural interventions or taxes were more influential on trial participants' shopping patterns.

2. Methods

2.1. Study design and participants

The Primary Care Shopping Intervention for Cardiovascular Disease Prevention (PCSHOP; Piernas et al., 2020) was a three-arm, parallel randomized controlled trial (RCT) to test the effect of brief advice alone or in combination with shopping feedback on SFA intake and shopping patterns of adults with raised low-density lipoprotein (LDL) after 3 months of intervention (Piernas et al., 2020). A sample of 113 individuals were recruited from GP practices in Oxfordshire (UK) and individually randomised, in a 1:3:3 ratio, to a 3-month intervention comprising: (i) no intervention (Usual Care; n = 17); (ii) general dietary advice (A; n = 48); and (iii) general dietary advice and personalised shopping advice (A + S; n = 48). The present study used a final sample of 111 participants due to the lack of shopping data in 2 people from the usual care and the general dietary advice groups. This study was reviewed and approved by the National Health Service Health Research Authority (HRA) Research Ethics Committee (Ref: 17/SC/0168).

2.2. Intervention groups and control

One intervention group received general dietary advice (A), consisting of a single ten-minute session with a healthcare professional on reducing saturated fat intake based on the British Heart Foundation "Cut the Saturated Fat" booklet. The second intervention group received general dietary advice plus shopping feedback (A + S), including the same brief advice session as well as personalized feedback on food shopping through a monthly report on their household food purchases during the intervention period. The shopping report included the mean weekly SFA content of their shopping plus specific suggestions for foods containing less SFA as swaps for frequently purchased high SFA foods, based on data from their supermarket loyalty card. The control group received no intervention but were informed of their blood test results by letter and invited to a follow up check at the end of the 3 month period. Table 1 summarises the main characteristics of participants per treatment group. Characteristics are not significantly different across groups, except for group $A + S$ being slightly younger than group A on average.

Table 1
Characteristics of participants per treatment group.

		Treatment group		
		Control	A	A + S
Age (avg.)		62.9[ab]	64.8[a]	59.9[b]
Body mass index (avg.)		26.4[a]	26.9[a]	27.8[a]
Sex[†]	Male	6	14	16
	Female	10	33	32
Educ. [†]	None	1	9	6
	Secondary	6	21	22
	Higher	9	17	20
HH Size[†]	1 person	3	7	9
	2 people	7	30	21
	3 people	5	3	8
	4 people	0	5	5
	5 + people	1	2	5

† No significant difference between treatment groups according to chi-squared test: p-value = 0.83, 0.56 and 0.18 for sex, education, and household size, respectively.

2.3. Shopping data

The trial collected individuals' shopping data from loyalty cards over the 3 months before and for about 3 months after the intervention. Loyalty card data on all recorded food purchases was individually-matched at the food level to the nutritional content, including kcal/kJ, SFA, total fat, sugars, salt and fiber, of the foods purchased as well as prices and volume size using a database of approximately 20,000 food products (Brand View Limited). We matched this data as it was not available from the loyalty card data. For nutritional content, values were expressed in grams per 100 g of the product. We selected major food groups that contributed the most to the amount of saturated fat in shoppers' baskets: meat, spreads, dairy, and cakes/biscuits (Piernas et al., 2020).

The original data detailed purchases in each trip to the supermarket, but this was aggregated to weekly purchases to increase its representativeness of an individual's regular purchase patterns. Therefore, an observation is defined as the basket of products purchased by an individual during a week, as well as the price and nutritional characteristics of those products. Table 2 summarises the number of individuals, their observed number of trips to the supermarket, and their number of observed weeks (observations) in the database for each treatment group. There is no significant difference between the number of supermarket trips per week depending on treatment group (p-value of Anova 0.22) or period (p-value of Anova 0.13). Concerning the number of weeks observed, there are no differences across treatment groups (p-value of Anova 0.44), but there are more weeks observed in the pre-treatment period than in the post-treatment period (p-value of Anova < 0.01). This is not a problem, though, as model parameters are not biased due to unbalanced data (though their significance could be reduced).

Each product in the database could be available in different formats, with varying weight and price. For example, Mozzarella comes both in 125-gram and 250-gram packages, with the second not twice as expensive as the former. But the database lacked that level of detail, instead aggregating all formats into a single product. To overcome this limitation, we expressed the purchased volume on grams (as opposed to units) and used the average price per gram throughout the whole study period. Hence, for modelling purposes, prices per gram of product are assumed to remain stable throughout the study period. Table 3 summarises the weekly spending (in GBP) for each treatment group. There are no significant differences in total expenditure between the pre and post periods for any of the treatment groups (p-value of Anova 0.76), but the control group does spend less than the others (p-value of Anova $<$ 0.01).

A tax on saturated fat was modelled based on the original policy of 16

Table 2
Summary of individuals, supermarket trips, and observations.

	Indivs.	Shoppingtrips	Weeks(obs.)	Avg. trips per week			Avg. weeks per indiv.		
				Total	Pre	Post	Total	Pre	Post
Control	16	941	454	2.1	2.0[a]	2.2[a]	28.4	17.9[a]	11.6[b]
A	47	2189	1180	1.9	1.8[a]	1.9[a]	25.1	13.7[a]	12.2[b]
A + S	48	2232	1271	1.8	1.7[a]	1.8[a]	26.5	16.1[a]	11.7[b]
Total	111	5362	2905	1.9	1.8	1.9	26.2	15.3	11.9

Table 3
Summary of spending (in GBP).

	Spending per week			Average weekly expenditure				
	Total	Pre	Post	Meat	Spreads	Dairy	Cake	Other
Control	38.0	40.0[a]	35.2[a]	5.7	0.7	4.3	3.4	24.9
A	45.5	44.6[b]	46.4[b]	4.4	1.0	4.7	4.0	32.3
A + S	45.6	45.9[b]	45.1[b]	5.6	0.8	4.6	3.9	31.6
Total	44.3	44.4	44.2	5.1	0.9	4.6	3.9	30.9

DKK/kg saturated fat when saturated fat exceeded 2.3 g/100 g (Smed et al., 2016). £1.70/kg was applied to eligible items by increasing the price of those goods in the data. Table 4 presents the average nutrient concentration in each product category, as well as their average observed price and its price after the proposed tax.

2.4. The multiple discrete-continuous extreme value (MDCEV) model

The MDCEV model (Bhat, 2008; Lu et al., 2017; Bhat, 2018) is an extension of the discrete choice model used commonly in shopping behaviour (e.g. Manski and Salomon, 1987; O'Neill et al., 2014; Schmid and Axhausen, 2019; Biondi et al., 2019; Livingstone et al., 2020). More specifically, the *multiple* denotes that many alternatives, rather than just one, can be chosen; the *continuous* denotes an amount of consumption, not just a yes/no choice as in discrete choice models; and the *extreme value* refers to the type I extreme value assumption on the error term – as is the case for simpler discrete choice models that are typically multinomial logit. In this framework, each consumer had a weekly shopping budget which s/he/they allocated between a range of available products, in this case foods (i.e. the dependent variable). Then, the MDCEV analysed shopping budget allocations across the goods in the supermarket; and derived utilities for supermarket products (e.g. butter) based on their attributes (e.g. salt content). These utilities comprise both attraction effects (i.e. *what* products to consume) and satiation effects (i.e. governing the volume of each good purchased).

2.5. MDCEV model specification

The dependent variable was each individual's weekly shopping volume, in grams, on each available product. Based on this amount, we can calculate the amount of SFA in shoppers' baskets, which is the primary focus of our analysis.

Table 4
Average nutrients and price per product category.

	g of nutrients / 100 g of product			Price (£/Kg)	
	Carbohydrates	Salt	Saturates	original	with tax
Cakes and biscuits	50.49	2.03	10.94	9.64	9.83
Meat	3.50	5.89	7.24	8.92	9.04
Poultry	2.95	1.21	2.39	8.55	8.58
High fat cheese	1.82	1.80	21.18	10.86	11.22
Low fat cheese	4.02	1.42	10.92	9.56	9.74
High fat spread	0.55	1.41	47.89	6.21	7.03
Low fat spread	2.09	2.51	20.05	4.19	4.53
Milk and dairy	11.36	0.41	3.33	2.53	2.57
High fat yoghurt	12.72	0.16	3.67	4.89	4.94
Low fat yoghurt	8.66	0.14	0.64	3.72	3.72

Independent variables are food-category dummy variables, trial arm dummy variables, prices, and the nutrient content of individuals' purchasing. We focussed on modelling food-categories that contribute the most to saturated fat consumption: meat, spreads, dairy, and cakes/biscuits (Piernas et al., 2020) by including these as *inside goods* in the formulation, meaning that these goods each have specific parameters in the model to capture preferences for them. All remaining products were aggregated into an *outside good* which enters the model. Since product preferences are measured relative to each other, this setup allows us to use all of the data and focus on the main food groups related to saturated fat.

Each inside good has a dummy variable, and a parameter is estimated on that dummy variable capturing the preference for its food-category. In total, 594 individual products in the data were modelled by 20 food-category terms (see Appendix 3 for details). These are dummy variables that take the value of 1 for similar products, 0 otherwise, to group them together in that category; for example different high fat cheeses are grouped by "high fat cheese" dummy variable. These terms allow us to analyse preferences for the food groups of interest and to preserve degrees of freedom (as opposed to having separate dummy variables for all 594 products). Where appropriate, these were interacted with a term denoting whether the good was branded (otherwise own brand). Brand is used in this context as a proxy for quality, as two products (e.g. two kinds of biscuits) can belong to the same product category and have similar nutritional content, but differ substantially in quality as perceived by the consumer.

There are three trial arms: (i) no intervention (Usual Care); (ii) general dietary advice (A); and (iii) general dietary advice and personalised shopping advice (A + S). Interactions of food-category terms and trial arms allow us to measure the impact of the behavioural interventions (versus no intervention) on food-category purchasing.

Nutrient-specific preference parameters measure associations of nutrients and purchasing of products. Nutrient variables were interacted with trial arms to measure whether the associations of nutrients and purchasing were different across the arms of the trial.

Interactions of trial arms and the post-intervention period were included to avoid confounding treatments effects with time effects.

With the description of the variables, we now move to the mathematical formulation of the MDCEV model. Based on economic theory, and in keeping with simpler discrete choice models, individuals are assumed to maximise utility, in this case a direct utility function, $U(x)$. x is a vector of non-negative quantities of J goods purchased throughout a week, where $x = (x_1, x_2, \ldots, x_J)$, measured here in grams. Products belonging to the food-categories of interest, the inside goods, are indexed by $j > 1$. Other products were combined into a composite outside good ($j = 1$). Then, a utility function is defined in equation (1) below.

$$U_n(x) = \frac{1}{\alpha}\psi_1 x_{n1}{}^{\alpha} + \sum_{j=2}^{J}\frac{\gamma_j}{\alpha}\psi_{nj}\left(\left(\frac{x_{nj}}{\gamma_j}+1\right)^{\alpha}-1\right) \tag{1}$$

Where $U_n(x)$ is the utility derived from weekly shopping basket n. For each product j (except for the outside good), a set of parameters is estimated, which take on different roles in the MDCEV model (NB – we supressed the n (individual) subscript to make the exposition clearer):

- ψ_j is the marginal utility for (inside) food-product j at zero consumption, or simply the baseline utility for food-product j. A higher baseline utility increases the chance of purchasing food-product j (i.e. the discrete choice element of shopping behaviour). Food-products are assigned to food-categories variables which vary at the level of the food-category; food-categories are indexed with k (e.g. food-product j (say a specific high fat cheese) in food-category k (the food-category of "high-fat cheeses")). The baseline utility also depends on the attributes of the food-product z_{nj}. Attributes are indexed with l. A type I extreme value error term ε_{nj} results in $\psi_{nj}(z_{nj}, \varepsilon_{nj}) = e^{\beta' z_{nj} + \varepsilon_{nj}}$. Food-category variables and food-product attributes also vary by: pre- and post-period ($post_n$), trial arms (A_n and $(A+S)_n$), and whether the product is branded or a supermarket own brand ($Branded_j$). β is a column vector of estimated parameters comprising food-category constants, the effect of product attributes, and experimental arms in the trial. The normalisation of one base utility is required for estimation. In this case, the outside good is used for this purpose, $\psi_1 = 1$. Then, the base utility for inside good j is specified as equation (2) below.

$$\log(\psi_{nj}) = \beta_k + \beta_{k,post}post_n + \beta_{k,A}A_n + \beta_{k,A+S}(A+S)_n + \beta_{k,branded}Branded_j + \sum_l\left(\beta_l + \beta_{l,post}post_n + \beta_{l,A}A_n + \beta_{l,A+S}(A+S)_n\right)z_{jl} + \varepsilon_{nj} \tag{2}$$

Where β_k are food-category-specific constant terms, indexing k food-categories as defined in Piernas et al. (2020). l indexes product attributes (salt, carbohydrates, and saturated fat). $Branded_j$ is a dummy taking the value 1 if product j is not the supermarket own brand; 0 otherwise. $post_n$ is a dummy taking value 1 if shopping basket n belongs to the post treatment period (independent of treatment group); 0 otherwise. A_n is a dummy with value 1 if shopping basket n belongs to the basic advice treatment group; 0 otherwise. $(A+S)_n$ is a dummy taking value 1 if shopping basket n belongs to the basic advice and shopping advice treatment group; 0 otherwise. As each food-product j belongs to a single product-category k, only one set of parameters $\{\beta_k, \beta_{k,post}, \beta_{k,A}, \beta_{k,A+S}, \beta_{k,branded}\}$ will remain in the utility. z_{jl} is the amount of nutrient l in product j. ε_{nj} is an iid type I extreme value error term capturing random utility.

- γ_j is a satiation parameter for food-product j governing the continuous element of shopping behaviour (i.e. the continuous choice element of shopping behaviour). The inclusion of γ_j allows for corner solutions (i.e. 0 consumption of goods). Lower values of γ_j imply faster satiation and therefore lower consumption when the product is chosen. Higher values oppositely imply slower satiation and therefore higher consumption when the product is chosen. In this model, γ_j is specified as a function of food category-specific terms:

$$\gamma_j = \sum_{k=1}^{K}\gamma_k Category_{jk} \tag{3}$$

In this model all products j belonging to the same food-category k share the same parameter, i.e. the same satiation effect $\gamma_k \forall j \in k$.

- α is a satiation parameter that is constant across all products. This is consistent with Bhat (2008)'s α-γ formulation of the utilities. This is the preferred utility formulation in literature because is more numerically stable, and allows for the use of an efficient forecasting algorithm, as described in Pinjari & Bhat (2021).

From the utility function, an individual's maximisation problem for each product is as equation (4) below,

$$\begin{gathered}\max_{x_n}\frac{1}{\alpha}\psi_1 x_{n1}{}^{\alpha} + \sum_{j=2}^{J}\frac{\gamma_j}{\alpha}\psi_j\left(\left(\frac{x_{nj}}{\gamma_j}+1\right)^{\alpha}-1\right)\\ s.t.\ \sum_{j=1}^{J}x_{nj}p_{nj} = B_n\end{gathered} \tag{4}$$

Where p_{nj} is the price per gram of product j in shopping basket n. As the outside good represents all the money spent on goods that are beyond our interest, we set its price to 1 ($p_{n1} = 1$), making the volume of the outside good equal to its price, hence allowing us to ignore the total weight of all these products, and instead only needing to know the total amount spent on them (Bhat 2008). B_n was consumer n's shopping budget, which we assume equal to their observed total expenditure.

With the distributional assumption on ε_{nj}, a closed form expression for the likelihood of shopping basket n is shown below. Allowing for M chosen (i.e. consumed) goods from J available products, and rearranging the vector of consumption as $x_n = (x^*_{n1}, x^*_{n2}, \cdots, x^*_{nM}, 0, 0, \cdots, 0)$,

$$P_n(x^*_{n1}, x^*_{n2}, \cdots, x^*_{nM}, 0, 0, \cdots, 0) = \frac{1}{p_{n1}}\frac{1}{\sigma^{M-1}}\left(\prod_{m=1}^{M_n}f_{nm}\right)\left(\sum_{m=1}^{M_n}\frac{p_{nm}}{f_{nm}}\right)\left(\frac{\sum_{m=1}^{M_n}e^{\frac{V_{nm}}{\sigma}}}{\left(\sum_{j=1}^{J}e^{\frac{V_{nj}}{\sigma}}\right)^{M_n}}\right)(M_n-1)! \tag{5}$$

Where m indexes the new order of food-products, σ is an estimated scale parameter, $f_{nm} = \left(\frac{1-\alpha}{x_{nm}+\gamma_m}\right)$, $V_{n1} = (\alpha-1)ln(x_{n1})$ and for $j > 1$ $V_{nj} = \beta' z_{nj} + (\alpha-1)ln\left(\frac{x_{nj}}{\gamma_j}+1\right) - ln\left(p_{nj}\right)$.

All analyses were conducted using the Apollo package in R (Hess and Palma, 2019). Statistical significance used t-ratios (versus 0), with parameters retained with t-ratios in excess of +/-1.96.

2.6. Comparison of interventions: Simulations

Based on the estimated parameters, as with any model, it is possible to simulate the outcome. In this case, we predict the amount of each good purchased in each week for each individual. If we hold the data constant except to vary one of the variables, we can simulate the impact of that variable on the outcome. For example, if we set the dummy variable for being in the dietary advice group to 0, we would get one prediction of purchasing. If we then set the variable to 1 and predicted again, we would get a second prediction of purchasing. Assuming all else was held equal in the model, this comparison tell us the model's impact of being in the dietary advice group versus not being in the dietary advice group. We can do this for a set of variables to retrieve the model's predictions of both the trial and increased prices on shopping purchases. This follows the procedure of Pinjari and Bhat (2021).

More specifically, simulating the impact of the interventions and taxes (and combinations) involves several steps. First, a simulation is made for no intervention, which is the fitted model's prediction of shoppers' current baskets. We refer to this as the *no intervention scenario*. Then, five additional simulations were made using the fitted model:

(i) *General dietary advice scenario (A)*: the estimated effect of the A treatment arm is applied to all observations (i.e., the dummy variable for arm A is set to 1 for all observations; Usual Care and $A + S$ are set to 0);
(ii) *General dietary advice and shopping advice scenario ($A + S$)*: the estimated effect of the A + S treatment arm is applied to all observations (i.e., the dummy variable for arm $A + S$ is set to 1 for all observations; Usual Care and A are set to 0);
(iii) *Saturated fat tax scenario (T)*: A tax equivalent to the Danish fat tax is applied to selected products by manipulating prices in the dataset – that is, a tax of £1.70 per 1000 g of saturated fat when fat exceeded 2.3 g/100 g (i.e., the price variable for goods that exceed the threshold is increased proportionally according to its fat content; Usual Care, A, and $A + S$ are as they were in the original data);
(iv) *General dietary advice and fat tax scenario ($A + T$)*: the combined effect of (i) and (iii); and
(v) *General dietary advice, shopping advice, and fat tax scenario ($A + S + T$)*: the combined effect of (ii) and (iii).

Finally, the impacts of simulations on the total amount of saturated fat in shoppers' baskets were compared. These were computed with the average marginal effects in equation (6).,

$$AME_{Int,k} = \frac{1}{N}\sum_{n} SFA_{Int,k,n} - SFA_{basescenario,k,n} \tag{6}$$

Where $AME_{Int,k}$ is the average marginal effect of intervention *Int* on the saturated fat content of shoppers' baskets in food-category k. *Int*, short for "intervention", is the set of scenarios (i)-(v). $SFA_{Int,k,n}$ is the amount of saturated fat in shopping basket n in scenario *Int* for food-category k. $SFA_{basescenario,k,n}$ is the amount of saturated fat in shopping basket n in the *no intervention scenario* for food-category c. AMEs were computed in both absolute terms (g of saturated fat in shoppers' baskets) and percentage terms.

Since prices are embedded in the model through the budget constraint, no explicit parameter on price is estimated. Nevertheless, it is possible to simulate the effect of price changes, since prices influence the forecasted consumption through the budget allocation.

3. Results

3.1. Baseline characteristics

The characteristics of the sample in the study are presented in Table 5. The average age of individuals was 62.4 years; and the average BMI was 27.2 kg/m2. Individuals were mostly female (Male = 32 %), had not attained higher education (Education: Higher = 41 %), and lived in households of on average more than 2 persons (Household size = 2.41).

3.2. MDCEV model estimates

The estimated MDCEV model and its diagnostic information are presented in Table 6. Food-category constant terms measure the utility for that food category and govern the discrete choice of whether an item in that category is purchased or not. Due to the highly non-linear form of the model, the absolute values of the parameters do not have a direct interpretation. However, they do reflect the probability that the food category was purchased (i.e. preferences): relatively higher estimates, ceteris paribus, mean higher utility and that those categories were more likely to have been purchased. Bakery items (*Bakery*: −4.12, 95 %CI: −4.45, −3.78) were more likely to have purchased than puddings (*Pudding*: −5.53, 95 %CI: −5.88, −5.26). The branded interaction terms represent any additional utility if a food-category is branded versus own brand: branded bakery items were, all else equal, less likely to have purchased than own brand (*Bakery * Branded*: −1.71, 95 %CI: −1.93, −1.49). The effects of the trial on food category preferences were captured in the interactions of trial arms and food-category. For example, individuals in the BASA arm are less likely to have purchased Milk than those that were not in the BASA arm (*Milk * A + S*: −0.42, 95 %CI: −0.79, −0.05). (NB: not all combinations are present because the model went through several stages of refinement where non-significant parameters were removed for parsimony.)

Nutrient parameters were estimated on continuous variables, representing per-unit associations between nutrients and utility; for example, foods with higher salt content were less likely to have purchased (*Salt*: −0.022, 95 %CI: −0.026, −0.018).

The gamma parameters govern the continuous aspect of purchasing. Lower values represent lower volumes purchased; and higher values denote higher volumes purchased. Higher volumes of bakery items (*Gamma (Bakery)*: −0.40, 95 %CI: −0.42, −0.38) were purchased than baking items (*Gamma (Baking)*: −0.62, 95 %CI: −0.72, −0.52).

A model in which the trial arm interactions were interacted with both base utility (probability of purchasing the food category) and the gamma parameters (volume of the food category purchased) was not supported by the data. Therefore, a model that interacted trial arms with base utility was tested against a model interacted trial arms with gamma parameters. The former was preferred. Our interpretation of these results is that the mechanism through which trial is impacting on behaviour is through the choice to purchase food categories rather than through the amount of food categories purchased.

Table 5
Descriptive statistics of individuals in sample.

	Full Sample		A		A + S		Usual Care	
	Mean	s.d.	Mean	s.d.	Mean	s.d.	Mean	s.d.
Age at baseline	62.4	10.9	64.8	9.25	59.9	11.71	62.9	11.5
Male (%)	32		29		33		38	
BMI at baseline	27.2	4.67	26.9	3.99	27.8	5.21	26.4	4.89
Education: Higher (%)	41		36		42		56	
Households size	2.41	1.24	2.31	1.24	2.52	1.27	2.38	1.2
N	111		47		48		16	

Table 6
MDCEV model estimates.

	Estimate	Rob.std. err.	Rob.t-ratio (0)	P-value
Food-category base utility and interactions				
Bakery	−4.12	0.17	−24.03	<0.001
Bakery * Branded	−1.71	0.11	−15.76	<0.001
Baking	−5.5	0.19	−28.83	<0.001
Baking * Branded	−0.62	0.17	−3.67	<0.001
Biscuit	−4.23	0.24	−17.34	<0.001
Biscuit * Branded	−1.35	0.14	−9.3	<0.001
Pudding	−5.53	0.14	−38.21	<0.001
Pudding * Branded	−0.6	0.15	−4.12	<0.001
Pudding * A	−0.67	0.18	−3.72	<0.001
Chocolate Bar	−4.3	0.25	−16.94	<0.001
Chocolate: Other	−5.39	0.2	−27.57	<0.001
Ice Cream	−5.11	0.21	−24.55	<0.001
Ice Cream * Branded	−1.09	0.2	−5.53	<0.001
Cheese: High fat	−4.19	0.13	–32.61	<0.001
Cheese: High fat * Branded	−1.14	0.17	−6.58	<0.001
Cheese: Low fat	−4.97	0.1	−47.81	<0.001
Cheese: Low fat * Branded	−0.81	0.09	−8.9	<0.001
Milk	−3.62	0.11	–33.62	<0.001
Milk * Branded	−3.65	0.25	−14.65	<0.001
Milk * Post	0.34	0.15	2.24	0.025
Milk * A	−0.41	0.19	−2.2	0.028
Milk * A + S	−0.42	0.19	−2.24	0.025
Milk Alternative	−6.91	0.22	−31.48	<0.001
Milky	−5.07	0.14	−35.03	<0.001
Milky * Branded	−1.52	0.22	−6.91	<0.001
Milky Alternative	−8.63	0.4	−21.63	<0.001
Yoghurt	−4.72	0.15	−31.03	<0.001
Yoghurt * Branded	−1.27	0.13	−9.45	<0.001
Spreads	−4.63	0.18	−26.37	<0.001
Spreads * Branded	−1.58	0.16	−9.65	<0.001
Poultry Por	−3.63	0.09	−40.99	<0.001
Poultry Por * Branded	−2.37	0.31	−7.71	<0.001
Poultry Pro	−4.4	0.13	–33.11	<0.001
Poultry Pro * Branded	−1.8	0.27	−6.66	<0.001
Red Meat Pro	−3.44	0.09	−38.66	<0.001
Red Meat Pro * Branded	−3.01	0.13	–22.34	<0.001
Red Meat Por	−4.39	0.11	−38.62	<0.001
Red Meat Por * Branded	−4.66	0.85	−5.51	<0.001
Red Meat Minced	−4.26	0.12	−34.47	<0.001
Product nutrient utility and interactions				
Carb	−0.01	0	−3.61	<0.001
Salt	−0.02	0	−9.82	<0.001
Salt * A	−0.02	0.01	−2.86	0.004
Saturated fat	0.02	0	7.16	<0.001
Saturated fat * A + S	−0.01	0	−3.15	0.002
Gamma estimates: satiation				
Gamma (Bakery)	0.4	0.01	29.49	<0.001
Gamma (Baking)	0.62	0.05	11.35	<0.001
Gamma (Biscuit)	0.36	0.02	22.31	<0.001
Gamma (Pudding)	0.46	0.03	17.21	<0.001
Gamma (Chocolate Bar)	0.27	0.03	8.37	<0.001
Gamma (Chocolate: Other)	0.29	0.02	15.8	<0.001
Gamma (Ice Cream)	0.91	0.05	19.34	<0.001
Gamma (Cheese: High fat)	0.53	0.02	22.62	<0.001
Gamma (Cheese: Low fat)	0.3	0.01	23.12	<0.001
Gamma (Milk)	1.99	0.13	15.37	<0.001
Gamma (Milk Alternative)	2.09	0.27	7.78	<0.001
Gamma (Milky)	0.44	0.02	20.62	<0.001
Gamma (Milky Alternative)	0.46	0.21	2.22	0.026
Gamma (Yoghurt)	0.85	0.05	18.05	<0.001
Gamma (Spreads)	0.63	0.03	20.11	<0.001
Gamma (Poultry Por)	1.25	0.08	15.44	<0.001
Gamma (Poultry Pro)	0.67	0.06	11.69	<0.001
Gamma (Red Meat Pro)	0.46	0.02	23.47	<0.001
Gamma (Red Meat Por)	0.91	0.06	15.79	<0.001
Gamma (Red Meat Mince)	0.79	0.06	12.24	<0.001
Alpha: base	−14.83	0.09	−168.23	<0.001
Sigma	0.84	0.02	54.08	<0.001
Model diagnostics				
No. of observations	2,905			
No. of estimated parameters	66			
LL(Fitted model)	−77,224.93			
AIC	154,581.90			
BIC	154,976.10			

Model was refined to retain only statistically significant parameters. Rob.std.err: Robust standard error. Rob.t-ratio(0): Robust t-ratio (estimate versus 0). Branded: branded interaction with food-category. A: General dietary advice interaction. A + S: General dietary advice and shopping advice interaction. LL – Log-likelihood; AIC Akaike Information Criteria; BIC Bayesian Information Criteria. (NB: not all combinations are present because the model went through several stages of refinement where non-significant parameters were removed for parsimony.)

3.3. *MDCEV model simulations*

Fig. 1 and Table 7 show the simulations of scenarios (i)-(v). All interventions resulted in reductions in saturated fat purchases, though of different magnitudes. The largest reductions in saturated fat in shopping baskets were predicted in scenarios (ii) and (v) involving the A + S treatment. The largest reduction was predicted in scenario (v) with the joint effect of A + S + T (−84.6 g; 95 %CI: −114.3 to −56.8 g; 24.7 % reduction). In descending order, reductions were predicted in scenario (ii) with A + S (−62.7 g; 95 %CI: −95.7 to −32.8 g; 18.5 % reduction), A + T (−42.0 g; 95 %CI: −48.7 g to −35.5 g; 13.2 % reduction), followed by T (−29.3 g; 95 %CI: −32.3 g to −26.1 g; 8.5 % reduction). The smallest reduction was A (−12.2 g; 95 %CI: −18.3 g to −5.3 g; 4.6 % reduction).

The greatest reductions in saturated fat were predicted for purchases of high fat spreads (–32.2 g; 95 %CI: −51.2 g to −13.8 g) and dairy products (−15.5 g; 95 %CI: –22.6 g to −7.5 g). Smaller reductions, around 5 g of saturated fat per weekly shop, were predicted in cakes/biscuits, high fat cheeses, and low fat spreads.

4. Discussion

A promising modelling technique in food behaviours was used with a randomized controlled trial and merged price/nutritional data to analyse shopping behaviours of 111 trial participants. Comparative analyses of a set of interventions showed that personalised shopping advice in combination with a tax was predicted to be the most effective strategy to reduce the amount of saturated fat in these shoppers' baskets. Personalised shopping advice by itself was next effective; offering general advice alone was least effective among the interventions. The greatest effects were predicted in high fat spreads and dairy products which are some of the largest contributors to the amount of saturated fat consumed in the UK (Public Health England, 2020; Pot et al., 2012). Our results suggest that the mechanism through which trial is impacting on behaviour is through the choice to purchase food categories rather than through the amount of food categories purchased, which follows from using the MDCEV model.

This study extends the results of the PCSHOP randomized controlled trial on shoppers' behaviours by jointly modelling the causal effects from a clinical trial of behavioural interventions with and without a hypothetical tax scenario. To our knowledge, this is the first study to directly compare a hypothetical tax with behavioural interventions delivered in routine care settings. By merging the data with product-specific nutritional information and prices, the resulting data contains rich information on the products that were purchased.

This is the first health application of the MDCEV model capable of jointly modelling the trial arms and the products' features (prices, nutrients, etc.). This allowed comparisons of the likely impact of policy scenarios which extended the knowledge generated from the trial. In addition, the framework accommodates both deterministic heterogeneity with individual characteristics, and random heterogeneity (i.e. controlling for unobserved, individual-specific preference variation). The advantages over standard discrete choice models used in these contexts are the modelling of the joint purchase of multiple items and the amounts of goods purchased. This model overcomes issues with alternative approaches. For example, AIDS models (Deaton and Muellbauer, 1980) are known to struggle with corner solutions (i.e. non-

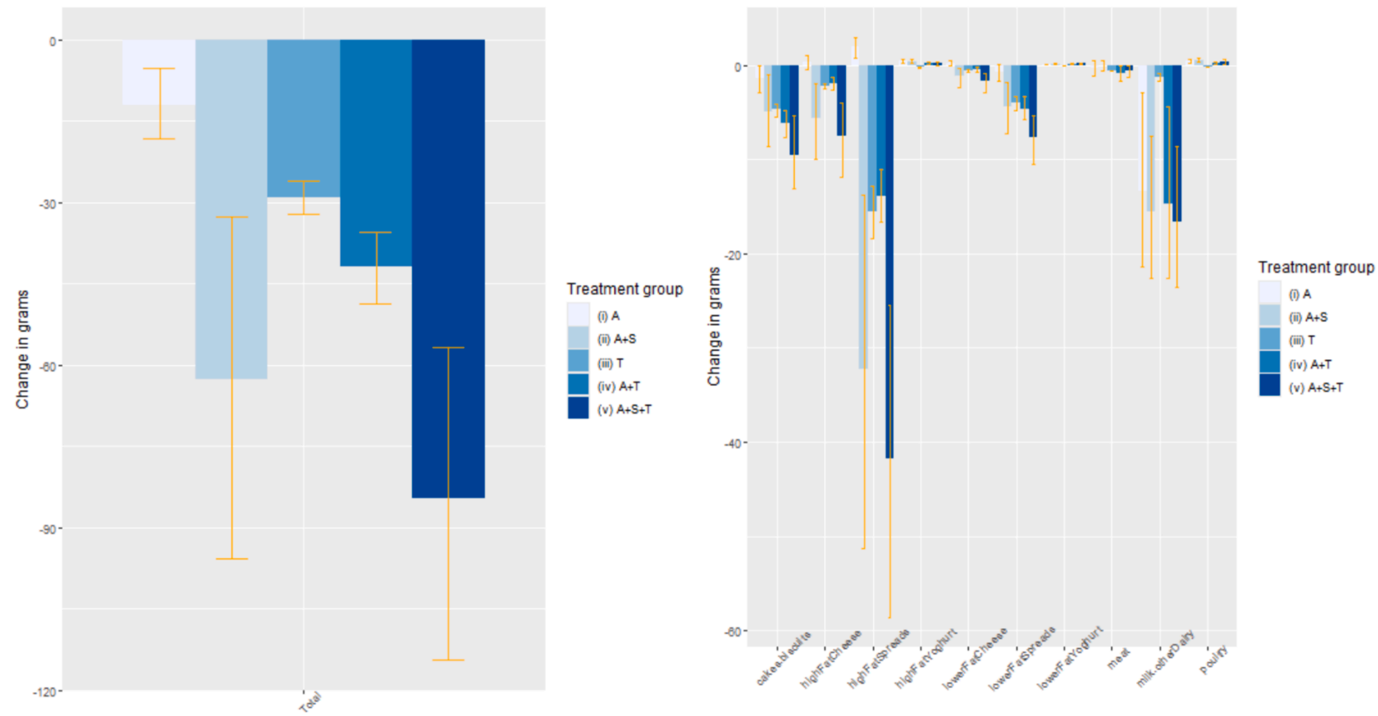

Fig. 1. Average Marginal Effects of scenarios (i)-(v) on the saturated fat content of shoppers' baskets, expressed in grams (g), as total (left) and by food category (right). A: *General dietary advice scenario; A + S: General dietary advice and shopping advice scenario; T: Saturated fat tax scenario; A + T: General dietary advice and fat tax scenario; A + S + T: General dietary advice, shopping advice, and fat tax scenario (A + S + T).*

trading of goods), while they are a natural component of MDCEV models.

Whilst we have rich data at the individual level, we recognize a number of limitations. First, by a small sample size. Second, by the recruitment of individuals only in the Oxfordshire area, which limits the representativeness of the sample. Due to these features, the extent to which our results are generalizable beyond this sample is unclear. However, we emphasize that selecting individuals based on raised LDL is useful for policy, because policies aimed at CVD prevention are most important for these individuals. There is the potential for a Hawthorne effect (Catalogue of Bias Collaboration, 2017). Shoppers could, after receiving advice, purchase more of healthier foods because they felt they ought to for being part of the trial. In this case, our results could overstate what might be expected in reality from advice-based interventions. As with standard MDCEV models of purchasing, the budget is assumed. In this case, the assumption is that the budget corresponds to the amount of money spent by each individual shopping for groceries over a week. However, given that this is revealed preference data using shoppers' own income (i.e. not given to them as part of the trial), we do not believe that this assumption is problematic. Moreover, the model assumes that the budget is constant and so that shoppers are reallocating their budget in response to the interventions. Of course, they might in reality simply purchase fewer items without substitution. Formulations of the utility function including interactions between product attributes and individual's characteristics were tested, but were not found to be statistically significant. Whilst this may seem surprising, we note that while we observe 2,095 weekly shopping baskets, all of them come from just 111 individuals, providing little variation on sociodemographic characteristics. Further, the sample only included adults with raised LDL, further reducing its variance. Finally, a significant limitation is the use of simulation for modelling demand. Whilst common, it is subject to many limitations. Here, for example, demand response is estimated by observing how behaviour changes for variations in the price of individual products (and these are mostly small promotions, i.e. lower prices), whereas taxes raise the price of multiple products at the same time, and these can be much higher. Unless the impact of price changes on demand is linear and symmetric, predictions from demand models are biased. Second, tax interventions aimed at promoting health embed a communication/signalling effect which might produce results beyond the mere price effects that we do not capture.

Compared to a previous estimate of a 4 % reduction in SFA due to a Danish fat tax (Smed et al., 2016), we found a heightened impact of the same tax, ~8.5 %, in this scenario. However, the data differ in origin, time, and analytical methods and so a direct comparison is inappropriate. Elsewhere, previous evidence considers total energy intake rather than specifically SFA purchasing (Eyles et al., 2012), and is thus not comparable to our estimates.

We found significant effects of the intervention for the group A and A + S that were not found to be statistically significant in the main trial (Piernas et al., 2020). This is due to several factors, partly driven by controlling for the no intervention post-intervention period in the MDCEV specification that isolated the effect of the treatments in the post-period. In addition, the form of the data was different in our analysis as we considered weekly shops (hence 2,905 observations here rather than 226 in Piernas et al. (2020); and pricing and product nutrient information were added to the data for these analyses.

Further research is needed to understand the financial implications of these interventions to business and to society. The personalised feedback brings costs to business, while taxation would increase government revenue, but at increased cost to consumers and may be regressive. Public acceptability of interventions is also a key factor in securing business or political leadership to intervene. Evidence shows that taxation is relatively unpopular compared to other policy options (Lancsar et al., 2022) and one of the reasons for the repealing of the Danish fat tax was public antipathy (Vallgårda et al., 2015). In contrast the personalised swaps proved popular with participants in the original research study, though this may overestimate the acceptability to the population as a whole.

In conclusion, we show how the MDCEV model can be applied to randomized controlled trials where the RCT data have been merged with

Table 7
Average Marginal Effects of scenarios (i)-(v) on the saturated fat content of shoppers' baskets, expressed in grams (g) and percentages (%).

	Scenario (i): A (g)	Scenario (ii): A + S (g)	Scenario (iii): T (g)	Scenario (iv): A + T (g)	Scenario (v): A + S + T (g)	Scenario (i): A (%)	Scenario (ii): A + S (%)	Scenario (iii): T (%)	Scenario (iv): A + T (%)	Scenario (v): A + S + T (%)
Total (mean)	−12.18	−62.75	−29.27	−42.01	−84.56	−4.60	−18.48	−8.45	−13.17	−24.70
Total (LCB)	−18.30	−95.72	−32.26	−48.67	−114.40	−6.76	−27.15	−8.93	−15.38	−32.31
Total (UCB)	−5.30	−32.79	−26.11	−35.48	−56.82	−2.15	−9.93	−7.82	−11.04	−16.98
cakes.biscuits (mean)	−1.35	−5.00	−4.71	−6.12	−9.49	−2.23	−6.82	−5.90	−8.15	−12.31
cakes.biscuits (LCB)	−2.88	−8.60	−5.42	−7.62	−13.09	−4.15	−11.72	−6.17	−10.01	−16.90
cakes.biscuits (UCB)	0.00	−0.95	−4.14	−4.82	−5.30	−0.46	−1.63	−5.67	−6.32	−7.34
highFatCheese (mean)	0.33	−5.58	−2.20	−1.89	−7.49	0.84	−17.87	−7.07	−6.26	−23.45
highFatCheese (LCB)	−0.47	−9.99	−2.44	−2.67	−11.85	−2.47	−28.40	−7.31	−9.20	−33.21
highFatCheese (UCB)	1.04	−2.01	−1.97	−1.20	−3.98	3.04	−7.30	−6.74	−4.33	−13.64
highFatSpreads (mean)	2.01	−32.19	−15.59	−13.96	−41.71	5.62	−43.82	−22.23	−20.37	−55.75
highFatSpreads (LCB)	0.81	−51.23	−18.34	−16.57	−58.61	0.30	−62.09	−22.68	−22.16	−70.16
highFatSpreads (UCB)	2.95	−13.83	−12.81	−11.00	−25.42	5.44	−22.69	−21.74	−19.07	−39.12
highFatYoghurt (mean)	0.45	0.42	−0.21	0.24	0.20	5.60	5.15	−2.30	3.12	2.73
highFatYoghurt (LCB)	0.27	0.22	−0.25	0.06	0.02	2.81	2.41	−2.77	0.09	−0.22
highFatYoghurt (UCB)	0.66	0.63	−0.17	0.43	0.38	9.09	6.93	−2.33	11.84	4.48
lowerFatCheese (mean)	0.22	−1.16	−0.61	−0.39	−1.74	1.15	−8.61	−4.30	−3.16	−12.45
lowerFatCheese (LCB)	−0.10	−2.29	−0.72	−0.73	−2.92	−1.52	−15.19	−4.51	−5.57	−18.75
lowerFatCheese (UCB)	0.50	−0.30	−0.50	−0.12	−0.86	3.48	−2.18	−4.09	−1.02	−6.36
lowerFatSpreads (mean)	−0.68	−4.38	−3.99	−4.65	−7.65	−3.90	−20.58	−17.89	−21.39	−33.69
lowerFatSpreads (LCB)	−1.64	−7.21	−4.80	−5.72	−10.55	−8.49	−32.18	−18.56	−25.59	−42.97
lowerFatSpreads (UCB)	0.07	−1.78	−3.28	−3.34	−5.31	0.61	−8.63	−17.17	−18.14	−23.83
lowerFatYoghurt (mean)	0.10	0.16	0.01	0.11	0.17	7.49	9.45	1.04	8.56	10.27
lowerFatYoghurt (LCB)	0.06	0.08	0.01	0.08	0.10	3.07	4.05	0.81	3.99	4.94
lowerFatYoghurt (UCB)	0.15	0.24	0.02	0.16	0.25	12.65	18.21	1.81	13.71	18.97
meat (mean)	−0.33	−0.01	−0.59	−0.90	−0.62	−1.47	−1.24	−1.91	−3.34	−3.17
meat (LCB)	−1.18	−0.62	−0.65	−1.72	−1.21	−4.10	−3.62	−2.00	−5.93	−5.54
meat (UCB)	0.50	0.53	−0.53	−0.07	−0.08	1.16	0.83	−1.84	−0.77	−1.13
milk.otherDairy (mean)	−13.38	−15.53	−1.21	−14.70	−16.57	−27.56	−32.02	−2.25	−30.05	−33.92
milk.otherDairy (LCB)	−21.41	−22.64	−1.67	−22.60	−23.53	−42.87	−45.79	−3.06	−45.08	−48.19
milk.otherDairy (UCB)	−2.96	−7.49	−0.87	−4.46	−8.61	−6.99	−14.75	−1.63	−9.92	−16.65
poultry (mean)	0.45	0.54	−0.18	0.27	0.35	3.84	3.98	−1.91	1.88	1.98
poultry (LCB)	0.26	0.31	−0.20	0.07	0.14	1.93	2.13	−2.06	−0.09	0.31
poultry (UCB)	0.60	0.78	−0.14	0.42	0.59	6.22	8.24	−1.71	4.27	6.33

Shopping basket totals and category-specific changes are presented. A: General dietary advice, scenario (i); A + S: General dietary advice and shopping advice, scenario (ii); T: Danish fat tax, scenario (iii); A + T: General dietary advice and Danish fat tax, scenario (iv); and A + S + T: General dietary advice, shopping advice, and Danish fat tax, scenario (v). Mean – mean AME; LCB – 95 % lower confidence bound of AME; UCB – 95 % upper confidence bound of AME.

other sources of data. This model overcomes issues associated with other approaches. It can accommodate multiple approaches (behavioural, taxation) when data are available; as well as individual and group-base preference variation. Whilst our data were subject to limitations, we believe that the MDCEV model can be a useful tool for answering important questions in food policy.

CRediT authorship contribution statement

John Buckell: Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **David Palma:** Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Stephane Hess:** Writing – review & editing, Methodology, Investigation, Conceptualization. **Susan A. Jebb:** Writing – review & editing, Supervision, Resources, Investigation,

Funding acquisition. **Carmen Piernas:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix 2. Linear model of food purchasing

As a comparator to the MDCEV model, a linear model was estimated by regressing the volume of each good purchased per week per individual on food categories, branding, experimental treatments, prices, foods' nutrients, and individual characteristics, including a random effect for individual, and fixed effects for time (as represented by season). Specifically,

$$x_{njw} = \beta_0 + \beta_{cat} foodcategory + \beta_{cat,bra} foodcategory{*}branded_j + \beta_{cat,treat} foodcategory{*}treatment + \beta_{treat} treatment + \beta_{price} price_{j,w} + \beta_{nut} nutrients_{j,w} + \beta_{nut,treat} nutrients_{j,w}{*}treatment + \beta_{ind} individualcharacteristics + \beta_{season}{*}season + \eta_n + \varepsilon_{j,w} \tag{a1}$$

Where x_{njw} is the volume of product j purchased in week w by individual n. *foodcategory* is a vector of the nine food categories used in the MDCEV model in the main results (e.g. meat). $branded_j$ is an indicator variable for if the product was branded (versus supermarket own brand). *treatment* is a categorical variable for the treatment arms in the experiment (and hence a vector of dummy variables). $price_{j,w}$ is the price of each product in week w. $nutrients_{j,w}$ is a vector of products' nutrients (carbohydrates, salt and saturated fat) for each product in each week. *individualcharacteristics* is a vector of individual characteristics (age, gender, BMI, and household size). *season* is a vectyor of dummy variables indicating the season of the year the observation belongs to. η_n is a random effect associated to individual n, it is assumed to follow a normal distribution with mean zero and a standard deviation to be estimated. $\varepsilon_{j,w}$ is an idiosyncratic error term assumed to follow a standard normal distribution, that is $\varepsilon_{j,w}\ iidN(0,1)$. By multiplying the number of individuals by the number of weeks and the number of available products in the dataset, a total number of observations in this model was 1,725,570. Table A2 below presents the estimates from the linear model specified in (a1).

Table A2
Estimates from linear model (dependent in grams).

		Estimate	t value
Intercept		19.5800	4.74
Individuals' characteristics	Age	0.0224	0.55
	BMI	−0.0211	−0.26
	Household size	0.9307	2.75
	Female	−0.6298	−0.79
	Random effect (s.d.)	3.5710	
Food category	High fat cheese	−9.9510	−14.78
	High fat spread	30.2700	10.35
	x branded	−37.1500	−13.05
	High fat yoghurt	22.4900	11.44
	x branded	−35.2900	−17.60
	Low fat cheese	−13.9900	−23.40
	Low fat spread	−5.7520	−6.24
	Low fat yoghurt	−12.3400	−17.28
	Meat	0.9095	1.27
	x branded	−16.3900	−21.14
	Milk and dairy	248.7000	221.36
	x branded	−254.5000	−229.31
	x summer	−6.1570	−5.41
	x winter	−2.5790	−2.02
	Poultry	27.3400	20.97
	x branded	−45.0700	−32.04
	x summer	−1.0470	−0.68
Time effects	Spring	0.1364	0.38
	Summer	−0.2169	−0.63
	Winter	0.3619	0.84
Price		−0.2678	−14.67
Treatment	post-treatment dummy	−0.6086	−1.03
	Advice (A)	0.2024	0.31
	x low fat yoghurt	5.3410	3.89

(*continued on next page*)

Table A2 (*continued*)

		Estimate	t value
	Advice and Rec. (A + S)	1.7460	2.34
	x poultry	5.9760	3.34
	x saturated fat	−0.0818	−2.58
Nutrient content (per 100 g)	Carbohydrates	−0.3007	−35.02
	Salt	−0.1607	−11.11
	Saturated fat	−0.2539	−11.52
Fit indices	R2 marginal	0.0421	
	R2 conditional	0.0427	

Results from the linear regression are reasonable. We observe that larger households buy more, while other individual characteristics are not significant, probably because the individual random effect captures most of these effects. In general, branded products are purchased in lower volumes than unbranded (i.e. own brand) products. Price has a negative effect on purchasing, as expected. The basic advice treatment encourages the purchase of lower fat yoghurt, but it does not have a significant effect on all products. The basic advice combined with the shopping advice, on the other hand, encourages the purchase of poultry, and decreases the appeal of saturated fat in all products. However, the combined basic and shopping advice causes an increase of volumes purchased overall.

While reasonable, the fit of the linear model is poor, reaching an R2 of only 4.2 %. This is likely due to the linear model assuming independence in the demand between products. Instead, the MDCEV model incorporates income effects due to its consideration of the budget (i.e. when one product is consumed more, the consumption of all other must decrease because the remaining budget decreases). The independence of demand between products is reflected on how the model captures the interventions favouring an increased consumption of lower-fat-yoghurt and poultry, but not a reduction on their fattier substitutes (high-fat-yoghurt and red meat, respectively). Table A3 presents the simulated AMEs for each of the interventions.

Table A3
Simulated AMEs from linear model.

	Effect in grams of saturated fat (g)					Effect in percentage of saturated fat (%)				
	BA	BASA	Tax	BA + Tax	BASA + Tax	BA	BASA	Tax	BA + Tax	BASA + Tax
Total	1.60	1.91	−0.15	1.48	1.78	154.7	67.5	−1.8	152.1	64.6
Cakes & biscuits	5.52	10.25	−0.42	5.22	10.01	17.3	32.3	−1.2	16.4	31.6
Red meat	3.75	2.53	−0.44	3.34	1.95	144.9	104.0	−14.1	135.0	79.9
Poultry	0.11	0.31	0.00	0.10	0.28	396.1	1845.7	−0.1	328.9	1816.7
High fat cheese	0.78	1.27	−0.05	0.72	1.20	0.7	1.2	0.0	0.6	1.1
Lower fat cheese	0.09	1.51	0.00	0.08	1.50	1.6	27.8	0.0	1.6	27.6
High fat spreads	0.90	1.92	−0.04	0.86	1.88	4.0	8.4	−0.2	3.8	8.2
Lower fat spreads	2.51	1.86	−0.43	2.20	1.66	31.3	29.8	−3.5	28.5	27.8
Milk and dairy	0.39	−1.05	−0.12	0.27	−1.18	1.9	−5.2	−0.6	1.3	−5.9
High fat yoghurt	1.91	0.23	0.00	1.91	0.23	1143.7	106.7	0.0	1143.7	106.7
Lower fat yoghurt	0.09	0.30	0.00	0.09	0.30	3.5	11.7	0.0	3.4	11.6

Finally, the average marginal effects (AME) predicted by the linear model are much smaller than the ones of the MDCEV. Again, this is likely due to the lack of interaction between demands for different products, as the increase in consumption of lower-fat products is not accompanied by a reduction in the consumption of their higher-fat substitutes, so effects average out. Furthermore, the linear model predicts many consumption levels very close to zero (or even negative, which must be truncated to zero), which makes the calculation of percentage changes numerically unstable, leading to unreasonable values.

Appendix 3. Product category aggregation

Base food category	num. prod.	Category		Base food category	num. prod.	Category	
		Modelling	Reporting			Modelling	Reporting
Cake Bites	7	bakery	cakes.biscuits	Cream	3	cheese2	cakes.biscuits
Cake slices	9	bakery	cakes.biscuits	Cream Alternatives	3	cheese1	cakes.biscuits
Cheesecake	2	bakery	cakes.biscuits	Dried milk	2	cheese2	cakes.biscuits
Croissants & Pastries	4	chocOth	cakes.biscuits	Milk	8	cheese2	cakes.biscuits
Doughnuts	3	chocOth	cakes.biscuits	Milk Alternatives	9	cheese2	cakes.biscuits
Fruit Bread & Teacakes	7	chocOth	cakes.biscuits	Milkshake Alternative	1	cheese2	cakes.biscuits
Muffins and Cupcakes	3	chocOth	cakes.biscuits	Milkshake Powder	1	cheese2	cakes.biscuits
Scones	2	chocOth	cakes.biscuits	Milkshakes	6	cheese2	cakes.biscuits
Sharing cake	7	chocOth	cakes.biscuits	Chicken Breasts/Portions	2	cheese2	cakes.biscuits
Tarts	1	chocBar	cakes.biscuits	Halal Chicken	1	cheese2	cakes.biscuits
Cooking Chocolate	5	chocBar	cakes.biscuits	Whole Chicken	2	cheese2	cakes.biscuits
Custard	4	chocOth	cakes.biscuits	Cooked Chicken/Poultry	3	cheese2	cakes.biscuits
Free From Confectionery	1	chocOth	cakes.biscuits	Poultry Sausage	4	cheese2	cakes.biscuits
Ready To Bake Pastries	2	chocOth	cakes.biscuits	Prepared Poultry	3	cheese2	cakes.biscuits
Sweet Cake Mixes	7	chocOth	cakes.biscuits	Turkey Bacon	1	milkyAl	cakes.biscuits
Cookies	11	chocOth	cakes.biscuits	Cream Cakes/Eclairs	1	milkyAl	cakes.biscuits
Free From Cakes & Biscuits	8	chocOth	cakes.biscuits	Free From Dessert	4	milky	cakes.biscuits
Other Biscuits	4	chocOth	cakes.biscuits	Frozen Desserts	9	milky	cakes.biscuits
Plain sweet biscuits	14	chocOth	cakes.biscuits	Fruit Pie	3	milkAlt	cakes.biscuits

(continued on next page)

(*continued*)

Base food category	num. prod.	Category Modelling	Reporting	Base food category	num. prod.	Category Modelling	Reporting
Sweet biscuits	27	chocOth	cakes.biscuits	Mousse	7	milk	cakes.biscuits
Blue Cheese	3	chocOth	cakes.biscuits	Packet Desserts & Whips	4	milky	cakes.biscuits
Brie & Camembert	5	chocOth	cakes.biscuits	Potted Dessert	8	milky	cakes.biscuits
Cheddar	14	chocOth	cakes.biscuits	Rice Pudding	4	poulPro	cakes.biscuits
Cheese Alternative	2	biscuit	cakes.biscuits	Sponge Pudding	6	poulPro	cakes.biscuits
Cheese Platter	1	baking	cakes.biscuits	Trifle	1	poulPro	cakes.biscuits
Cheese Sauce	2	baking	cakes.biscuits	Beef Mince	1	redMPro	cakes.biscuits
Cheese Slices	6	baking	cakes.biscuits	Lamb Mince	1	redMPro	cakes.biscuits
Cheese Wheel	2	bakery	cakes.biscuits	Meatballs	1	redMPro	cakes.biscuits
Cheese/Cream Dip	3	baking	cakes.biscuits	Pork Mince	2	redMPro	cakes.biscuits
Cottage Cheese & Quark	2	bakery	cakes.biscuits	Beef Joints	1	redMPro	cakes.biscuits
Feta & Greek Salad Cheese	2	bakery	cakes.biscuits	Beef Steaks	1	redMPro	cakes.biscuits
Free From Cheese	3	biscuit	cakes.biscuits	Lamb Fillets/Steaks	1	redMPro	cakes.biscuits
Goats Cheese	2	biscuit	cakes.biscuits	Lamb Joints	1	redMPro	cakes.biscuits
Grated Cheddar	5	biscuit	cakes.biscuits	Offal	2	redMPro	cakes.biscuits
Hard Cheese	4	pudding	cakes.biscuits	Pork Joints	2	redMPro	cakes.biscuits
Mozzarella	2	pudding	cakes.biscuits	Pork Steaks & Chops	3	redMPro	cakes.biscuits
Parmesan	1	pudding	cakes.biscuits	Stewing Meet	1	redMPro	cakes.biscuits
Sliced Cheddar	5	pudding	cakes.biscuits	Bacon	3	redMPro	cakes.biscuits
Snack Cheese	7	bakery	cakes.biscuits	Burgers	4	redMPro	cakes.biscuits
Soft Cheese	12	pudding	cakes.biscuits	Prepared Red Meat	5	redMPro	cakes.biscuits
Chocolate Bags	22	iceCrea	cakes.biscuits	Processed meat	10	redMPro	cakes.biscuits
Chocolate Bar Block	7	iceCrea	cakes.biscuits	Sausages	9	redMPor	cakes.biscuits
Chocolate Bars	50	pudding	cakes.biscuits	Tinned Meat	3	redMMin	cakes.biscuits
Chocolate Gifts	40	pudding	cakes.biscuits	Baking Butter	2	spreads	cakes.biscuits
Chocolate Spread	5	bakery	cakes.biscuits	Block Butter	9	spreads	cakes.biscuits
Ice Cream	10	cheese2	highFatCheese	Free From Butter	4	spreads	highFatCheese
Ice Cream alternative	1	cheese1	highFatCheese	Tub Butter	10	spreads	highFatCheese
Ice Cream tub	12	cheese1	highFatCheese	Flavoured yoghurt	27	yoghurt	highFatCheese
Ice Cream water based	10	cheese2	lowerFatCheese	Plain yoghurt	10	yoghurt	lowerFatCheese
Ice Cream yogurt based	1	cheese2	lowerFatCheese	Yoghurt Alternative	6	yoghurt	lowerFatCheese
				Yoghurt Drinks	10	yoghurt	lowerFatCheese

Appendix 4. MDCEV with post-stratification weighting

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Table A5
MDCEV model with post-stratification weights. Model was refined to retain only statistically significant parameters. Rob.std.err: Robust standard error. Rob.t-ratio: Robust t-ratio (estimate versus 0). Bra: branded interaction with food-category. Pst: post-intervention interaction term. BA: General dietary advice interaction. BASA: General dietary advice and shopping advice interaction.

Parameter	Estimate	Rob s.e.	Rob t-ratio
alpha_base	−20.738	0.100	−207.293
sigma	0.840	0.017	49.220
bakery	−4.021	0.216	−18.616
bakeryBra	−1.752	0.133	−13.185
baking	−5.524	0.190	−29.040
bakingBra	−0.606	0.169	−3.578
biscuit	−4.156	0.285	−14.573
biscuitBra	−1.333	0.136	−9.806
pudding	−5.511	0.154	−35.749
puddingBra	−0.596	0.165	−3.612
chocBar	−4.105	0.343	−11.967
chocBarBra	0.000	NA	NA
chocOth	−5.301	0.231	−22.968
chocOthBra	0.000	NA	NA
iceCrea	−5.004	0.235	−21.310
iceCreaBra	−1.198	0.213	−5.630
cheese1	−4.205	0.140	−30.118
cheese1Bra	−1.186	0.170	−6.959
cheese2	−4.926	0.112	−44.015
cheese2Bra	−0.849	0.096	−8.832
milk	−3.589	0.114	−31.429
milkBra	−3.759	0.244	−15.381
milkAlt	−6.838	0.279	−24.491
milkAltBra	0.000	NA	NA
milky	−5.118	0.158	−32.468

(*continued on next page*)

Table A5 (*continued*)

Parameter	Estimate	Rob s.e.	Rob t-ratio
milkyBra	−1.471	0.224	−6.565
milkyAl	−8.762	0.431	−20.310
milkyAlBra	0.000	NA	NA
yoghurt	−4.764	0.157	−30.369
yoghurtBra	−1.252	0.164	−7.643
spreads	−4.663	0.187	−24.946
spreadsBra	−1.533	0.188	−8.141
poulPor	−3.676	0.090	−40.712
poulPorBra	−2.236	0.361	−6.193
poulPro	−4.384	0.155	−28.349
poulProBra	−1.887	0.251	−7.508
redMPro	−3.445	0.105	–32.920
redMProBra	−3.095	0.128	−24.162
redMPor	−4.387	0.133	–32.922
redMPorBra	−4.463	0.850	−5.250
redMMin	−4.311	0.127	−34.076
carb	−0.014	0.004	−3.427
carbPost	0.000	NA	NA
carbBA	0.000	NA	NA
carbBASA	0.000	NA	NA
salt	−0.023	0.003	−9.120
saltPost	0.000	NA	NA
saltBA	−0.024	0.008	−2.993
saltBASA	0.000	NA	NA
satu	0.022	0.004	6.101
satuPost	0.000	NA	NA
satuBA	0.000	NA	NA
satuBASA	−0.011	0.003	−3.277
bakeryPost	0.000	NA	NA
bakeryBA	0.000	NA	NA
bakeryBASA	0.000	NA	NA
bakingPost	0.000	NA	NA
bakingBA	0.000	NA	NA
bakingBASA	0.000	NA	NA
biscuitPost	0.000	NA	NA
biscuitBA	0.000	NA	NA
biscuitBASA	0.000	NA	NA
puddingPost	0.000	NA	NA
puddingBA	−0.633	0.183	−3.456
puddingBASA	0.000	NA	NA
chocBarPost	0.000	NA	NA
chocBarBA	0.000	NA	NA
chocBarBASA	0.000	NA	NA
chocOthPost	0.000	NA	NA
chocOthBA	0.000	NA	NA
chocOthBASA	0.000	NA	NA
iceCreaPost	0.000	NA	NA
iceCreaBA	0.000	NA	NA
iceCreaBASA	0.000	NA	NA
milkPost	0.303	0.157	1.934
milkBA	−0.387	0.211	−1.836
milkBASA	−0.403	0.201	−2.003
gBakery	0.397	0.014	29.254
gBaking	0.615	0.049	12.460
gBiscuit	0.368	0.018	20.400
gPudding	0.454	0.029	15.632
gChocBar	0.301	0.045	6.742
gChocOth	0.304	0.024	12.880
gIceCrea	0.908	0.056	16.195
gCheese1	0.521	0.022	24.038
gCheese2	0.301	0.014	21.112
gMilk	1.976	0.138	14.287
gMilkAlt	2.185	0.319	6.840
gMilky	0.439	0.021	20.947
gMilkyAl	0.595	0.361	1.646
gYoghurt	0.867	0.052	16.736
gSpreads	0.644	0.033	19.335
gPoulPor	1.245	0.088	14.206
gPoulPro	0.681	0.060	11.335
gRedMPro	0.451	0.020	22.815
gRedMPor	0.916	0.055	16.538
gRedMMin	0.809	0.059	13.716

Appendix 5. Mixed MDCEV

One possible way to introduce variations of taste (preferences) among respondents is assuming that preference parameters follow a random distribution. This approach is common in the discrete choice model context (Train, 2009), and is the most used method in health-based choice modelling (Vass et al., 2022). In this setting, we assume that some of the parameters in the base utility (ψ_j) of alternatives follow a random distribution f (e.g. a normal distribution) with parameters mean μ_β and standard deviation σ_β. Then, the probability of observing a given weekly shopping basket would be as follows.

$$P_n\left(x_{n1}^*, x_{n2}^*, \cdots, x_{nM}^*, 0, 0, \cdots, 0\right) = \int_{-\infty}^{+\infty} P_n\left(x_{n1}^*, x_{n2}^*, \cdots, x_{nM}^*, 0, 0, \cdots, 0\right) f\left(\beta|\mu_\beta, \sigma_\beta\right) d\beta$$

The estimates from the mixed MDCEV model are presented below.

Table A6
Mixed MDCEV model estimates.

		ASC (mean)		ASC (s.d.)		Branded		Intervention		Satiation	
		Est.	t-ratio	Est.	t-ratio	Est.	t-ratio	Est.	t-ratio	Est.	t-ratio
Product categories	Bakery	−4.22	−50.81	0.44	6.89	−1.71	−26.35			0.40	46.86
	Baking	−5.74	−40.17	0.66	4.59	−0.62	−5.08			0.62	19.61
	Biscuits	−4.38	−43.38	0.56	8.37	−1.35	−22.75			0.36	40.76
	Pudding	−5.72	−68.27	0.61	6.63	−0.60	−7.58			0.46	28.89
	x Basic advice							−0.70	−4.90		
	Chocolate bar	−4.30	−45.30	−0.03	−0.55					0.27	19.57
	Chocolate other	−5.46	−58.83	0.40	4.48					0.29	33.08
	Ice cream	−5.32	−61.72	0.65	9.45	−1.10	−14.32			0.90	34.19
	Cheese 1	−4.19	−85.25	0.00	−0.22	−1.14	−17.66			0.53	46.24
	Cheese 2	−5.11	−89.05	0.52	9.64	−0.81	−16.02			0.30	48.71
	Milk	−3.61	−89.07	0.10	0.72	−3.65	−39.53			1.97	30.67
	x post intervention							0.33	4.07		
	x basic advice							−0.42	−4.55		
	x shopping advice							−0.42	−4.62		
	Creamy	−5.07	−83.03	−0.06	−1.85	−1.52	−14.96			0.44	29.54
	Yoghurt	−4.72	−96.10	−0.02	−1.08	−1.27	−26.75			0.85	49.83
	Spreads	−4.62	−63.56	−0.01	−0.97	−1.57	−25.46			0.64	46.28
	Poultry	−3.63	−99.42	0.04	1.14	−2.36	−15.34			1.25	31.88
	Red meat product	−3.48	−81.02	0.27	3.01	−3.01	−42.75			0.46	43.46
	Read meat portion	−4.46	−71.94	0.36	3.00	−4.65	−5.56			0.91	28.80
	Minced meat	−4.25	−85.28	−0.01	−0.20					0.79	30.89
Nutrients	Carbohydrates	−0.01	−9.15								
	Salt	−0.02	−15.22								
	x Basic advice							−0.02	−3.31		
	Saturated fats	0.02	17.05								
	x shopping advice							−0.01	−5.67		
Common parameters	Satiation (α)	0.03	(fixed)								
	Scale (σ)	−6.90	−96.37								
Fit	Loglikelihood			−77156.5							
	Number of parameters			85							
	Number of individuals			111							
	Number of observations			2905							

References

Andreyeva, T., Long, M.W., Brownell, K.D., 2010. The impact of food prices on consumption: a systematic review of research on the price elasticity of demand for food. Am. J. Public Health 100 (2), 216–222.

Aveyard, P., Lewis, A., Tearne, S., Hood, K., Christian-Brown, A., Adab, P., et al., 2016. Screening and brief intervention for obesity in primary care: a parallel, two-arm, randomised trial. Lancet 388 (10059), 2492–2500.

Bhat, C., 2008. The multiple discrete-continuous extreme value (MDCEV) model: role of utility function parameters, identification considerations, and model extensions. Transp. Res. B Methodol. 42 (3), 274–303.

Bhat, C., 2018. A new flexible multiple discrete–continuous extreme value (mdcev) choice model. Transp. Res. 110B, 261–279.

Biondi, B., Van der Lans, I.A., Mazzocchi, M., Fischer, A.R.H., Van Trijp, H.C.M., Camanzi, L., 2019. Modelling consumer choice through the random regret minimization model: an application in the food domain. Food Qual. Prefer. 73, 97–109.

Catalogue of Bias Collaboration, Spencer EA, Mahtani K, Hawthorne effect. In: Catalogue Of Bias 2017: https://catalogofbias.org/biases/hawthorne-effect/.

Cornelsen, L., Green, R., Turner, R., Dangour, A.D., Shankar, B., Mazzocchi, M., Smith, R. D., 2015. What happens to patterns of food consumption when food prices change? evidence from a systematic review and meta-analysis of food price elasticities globally. Health Econ. 24 (12), 1548–1559.

Deaton, A., Muellbauer, J., 1980. An almost ideal demand system. Am. Econ. Rev. 70 (3), 312–326.

Dodd, R., Santos, J.A., Tan, M., Campbell, N.R.C., Ni Mhurchu, C., et al., 2020. Effectiveness and feasibility of taxing salt and foods high in sodium: a systematic review of the evidence. Adv. Nutr. 11 (6), 1616–1630.

Eyles, H., Ni Mhurchu, C., Nghiem, N., Blakely, T., 2012. Food pricing strategies, population diets, and non-communicable disease: a systematic review of simulation studies. PLoS Med. 9 (12), e1001353.

Green, R., Cornelsen, L., Dangour, A.D., Turner, R., Shankar, B., Mazzocchi, M., Smith, R. D., 2013. The effect of rising food prices on food consumption: systematic review with meta-regression. BMJ : British Medical Journal 346, f3703.

Hartmann-Boyce, J., Bianchi, F., Piernas, C., Riches, S.P., Frie, K., Nourse, R., Jebb, S.A., 2018. Grocery store interventions to change food purchasing behaviors: a systematic review of randomized controlled trials. Am. J. Clin. Nutr. 107 (6), 1004–1016.

Hess, S., Palma, D., 2019. Apollo: a flexible, powerful and customisable freeware package for choice model estimation and application. J. Choice Model. 32, 100170.

Hooper, L., Martin, N., Jimoh, O.F., Kirk, C., Foster, E., Abdelhamid, A.S., 2020. Reduction in saturated fat intake for cardiovascular disease. Cochrane Database Syst. Rev.

Lancsar, E., Ride, J., Black, N., Burgess, L., Peeters, A., 2022. Social acceptability of standard and behavioral economic inspired policies designed to reduce and prevent obesity. Health Econ. 31 (1), 197–214.
Livingstone, K.M., Lamb, K.E., Abbott, G., Worsley, T., McNaughton, S.A., 2020. Ranking of meal preferences and interactions with demographic characteristics: a discrete choice experiment in young adults. Int. J. Behav. Nutr. Phys. Act. 17 (1), 157.
Lu, H., Hess, S., Daly, A., Rohr, C., 2017. Measuring the impact of alcohol multi-buy promotions on consumers' purchase behaviour. J. Choice Model. 24, 75–95.
Mach, F., C. Baigent, A. L. Catapano, K. C. Koskinas, M. Casula, L. Badimon, M. J. et al. (2020). "2019 ESC/EAS Guidelines for the management of dyslipidaemias: lipid modification to reduce cardiovascular risk: The Task Force for the management of dyslipidaemias of the European Society of Cardiology (ESC) and European Atherosclerosis Society (EAS)." European Heart Journal 41(1): 111-188.
Manski, C.F., Salomon, I., 1987. The demand for teleshopping: an application of discrete choice models. Reg. Sci. Urban Econ. 17 (1), 109–121.
Mizdrak, A., Scarborough, P., Waterlander, W.E., Rayner, M., 2015. Differential responses to food price changes by personal characteristic: a systematic review of experimental studies. PLoS One 10 (7), e0130320.
Niebylski, M.L., Redburn, K.A., Duhaney, T., Campbell, N.R., 2015. Healthy food subsidies and unhealthy food taxation: a systematic review of the evidence. Nutrition 31 (6), 787–795.
O'Neill, V., Hess, S., Campbell, D., 2014. A question of taste: recognising the role of latent preferences and attitudes in analysing food choices. Food Qual. Prefer. 32, 299–310.
Payne Riches, S., Piernas, C., Aveyard, P., Sheppard, J.P., Rayner, M., Albury, C., et al., 2021. A mobile health salt reduction intervention for people with hypertension: results of a feasibility randomized controlled trial. JMIR Mhealth Uhealth 9 (10), e26233.
Piernas, C., Aveyard, P., Lee, C., Tsiountsioura, M., Noreik, M., Astbury, N.M., et al., 2020. Evaluation of an intervention to provide brief support and personalized feedback on food shopping to reduce saturated fat intake (PC-SHOP): a randomized controlled trial. PLoS Med. 17 (11), e1003385.
Pinjari, A.R., Bhat, C., 2021. Computationally efficient forecasting procedures for Kuhn-Tucker consumer demand model systems: application to residential energy consumption analysis. J. Choice Model. 39.
Pot, Prynne, G.K., Roberts, C.J., Olson, C., Nicholson, A., Whitton, S.K., B., C., et al., 2012. National Diet and Nutrition Survey: fat and fatty acid intake from the first year of the rolling programme and comparison with previous surveys. Br. J. Nutr. 107 (3), 405–415. https://doi.org/10.1017/s0007114511002911.
Public Health England (2020). National Diet and Nutrition Survey Rolling programme Years 9 to 11 (2016/2017 to 2018/2019). London, Public Health England. Available online: https://www.gov.uk/government/statistics/ndns-results-from-years-9-to-11-2016-to-2017-and-2018-to-2019 accessed 16/02/2021.
SACN. 2021. SACN statement on nutrition and older adults living in the community. Available online: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/953911/SACN_Nutrition_and_older_adults.pdf accessed 16/02/2021.
Schmid, B., Axhausen, K.W., 2019. In-store or online shopping of search and experience goods: a hybrid choice approach. J. Choice Model. 31, 156–180.
Slapø, H., Schjøll, A., Strømgren, B., Sandaker, I., Lekhal, S., 2021. Efficiency of in-store interventions to impact customers to purchase healthier food and beverage products in real-life grocery stores: a systematic review and meta-analysis. Foods 10 (5).
Smed, S., Scarborough, P., Rayner, M., Jensen, J.D., 2016. The effects of the Danish saturated fat tax on food and nutrient intake and modelled health outcomes: an econometric and comparative risk assessment evaluation. Eur. J. Clin. Nutr. 70 (6), 681–686.
Teng, A.M., Jones, A.C., Mizdrak, A., Signal, L., Genç, M., Wilson, N., 2019. Impact of sugar-sweetened beverage taxes on purchases and dietary intake: systematic review and meta-analysis. Obes. Rev. 20 (9), 1187–1204.
Vallgårda, S., Holm, L., Jensen, J.D., 2015. The Danish tax on saturated fat: why it did not survive. Eur. J. Clin. Nutr. 69 (2), 223–226.
World Health Organization. 2020. https://www.who.int/news-room/fact-sheets/detail/the-top-10-causes-of-death. Accessed 15th January 2021.