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Food Price Elasticities for Policy Interventions: Estimates from a Virtual Supermarket Experiment in a Multistage Demand Analysis with (Expert) Prior Information

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Food price elasticities (PEs) are essential for evaluating the impacts of food pricing interventions to improve dietary and health outcomes. This paper innovates the use of experimental purchasing data from a recent New Zealand virtual supermarket experiment to estimate PEs for a large set of disaggregated foods across major food groups relevant for food policies in a Bayesian multistage demand framework. We propose the use of available prior information to elicit prior demand parameter assumptions that are consistent with published PEs and economic assumptions and are weighted according to expert knowledge, increasing precision in PE inference and policy predictions, and yielding somewhat stronger price effects.

I Introduction

Diet-related risk factors (e.g., obesity, low fruit and vegetable (F&V) intake, and high salt intake) now form the most important risk factor set for the global burden of disease, with poor diets estimated to be responsible for 9.6 per cent of the global burden of disease measured in disability adjusted life years (GBD 2016 Risk Factors Collaborators, 2017). Several countries have already introduced different types of food taxes and subsidies including Mexico and Hungary with junk food taxes, and France, Mexico and the UK with soft drink taxes (Batis *et al*., 2016; Briggs *et al*., 2017; Teng *et al*., 2019) with the aim to improve dietary and health outcomes. In this paper we provide an innovative demand analysis of a virtual supermarket (VS) experiment to estimate a comprehensive set of food price elasticities (PEs) across all major food groups, an essential input for the assessment and design of health policies (Cornelsen *et al*., 2015).

While the number of studies on food taxes and subsidies is growing rapidly given their increasing popularity, concerns regarding the quality of the evidence remains. A recent systematic review and meta-analysis points to the effectiveness of such measures, but has also identified a range of important limitations in the current evidence base

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on food PEs, mostly in relation to the validity of the data commonly used in studies estimating the effects of food taxes (Afshin *et al.*, 2017). Previous systematic reviews on food price simulation studies have also highlighted similar concerns, showing that the majority of included studies (25/32) were of low quality with a general lack of well-validated own-price elasticity (oPE) and cross-price elasticity (cPE) data (Eyles *et al.*, 2012; Laura *et al.*, 2015). Our proposed approach therefore combines the strengths of experimental settings, such as exogenous price variation, with additional information from large sample observational studies and expert knowledge to estimate PEs within a Bayesian demand system to address several limitations in the literature.

Two major limitations of the existing work on food PEs are price endogeneity when working at a market level (price and quantity are determined simultaneously by the interaction between demand and supply; Imbens, 2014), combined with a lack of price variation and range of food groupings. PE estimates are typically based on observational studies of how the consumption of broad food groups varies with 'natural' price variations over time, by region or following some natural experiment (Nghiem *et al.*, 2013). These 'natural' price variations may potentially be endogenous, due to prices and quantities being determined in partial equilibrium markets. With commonly only small variations in prices, resulting PE estimates are imprecise and often inconclusive, in particular regarding substitutionary versus complementary relationships (i.e., cPEs) which are key for policy analysis. Second, the reported food groupings are commonly not defined in terms of relevant health outcomes or pricing interventions (e.g., separating regular and diet soft drinks).

In this paper we therefore use an innovative randomised experiment of a VS that was designed at the population level to recreate a realistic shopping experience. Covering over 1,400 food items, it allows for the definition of food groups by nutrient and choice categories that are relevant to analyse health effects (Waterlander *et al.*, 2019). Importantly, it imposed random exogenous and substantial price variation. Although there are good examples of randomised control trials (RCT) directly testing the effects of specific healthy food subsidies (Waterlander *et al.*, 2019), without the estimation of PEs and substitution and complementing effects, insights into the impact of food taxes and subsidies remain limited. In addition, RCTs are generally carried out in a specific study population (Afshin *et al.*, 2017); and randomised trials of food price changes at the population level are uncommon (Ni Mhurchu *et al.*, 2009).

We add a further new dimension to the literature on food PEs by incorporating knowledge from previous observational studies (Ni Mhurchu *et al.*, 2013; Sharma *et al.*, 2014) via prior information within a Bayesian demand analysis. A similar strategy has been used in a recent study of oil price demand (Baumeister & Hamilton, 2019) and in the estimation of vector autoregressive models (VAR) to analyse macroeconomic dynamics (Jarociński & Marcet, 2019). The VAR literature has a long tradition of using available prior information to improve the identification and precision of parameter estimation and predictions for inference in highly parameterised models that are typically analysed using moderate size samples (Koop & Koribilis, 2010). Such a strategy exploits the probabilistic coherence associated with different information sources combined via Bayes rule, that is, sample and prior information, as well as the property of the Bayesian estimator being a shrinkage estimator (James & Stein, 1961).

We propose a carefully elicited prior on food demand coefficients that captures preferences relating to price and income effects. These prior assumptions are specified in the context of the linear almost ideal demand system (LAIDS), widely used in food demand analysis and PE estimation (Rickertsen *et al.*, 2003; Nghiem *et al.*, 2011; Kelhbacher *et al.*, 2020) due to its theoretical and empirical properties, and the evidence for linear food Engel curves (Banks *et al.*, 1997). The elicited prior is consistent with previous PE estimates and economic assumptions of a multistage Bayesian LAIDS model similar to the one considered in Briggs *et al.* (2013). This is a preferred strategy to address the inherent censoring issue when analysing demand for disaggregated foods across major food groups compared with the alternative of imputing budget shares for subjects with observed zero consumption (Tiffin & Arnoult, 2008; Kasteridis *et al.*, 2011; Bilgic & Yen, 2014). Further, since the best available previously published information is provided in terms of PEs estimates rather than demand equation coefficients, we introduce an optimisation procedure to convert values of PEs into prior location information on the demand parameters in the different demand (sub)systems taking into account over-identification. Hence, the approach also introduces an alternative to the Bayesian LAIDS analysis via default (non-informative) priors that are centred on zero, thus implying unitary oPEs, no substitution or complementary effects, and disregarding microeconomic restrictions.

In the empirical analysis we estimate a three-stage demand system and present inference around the PE matrix for 23 final food groups for the VS experiment. We propose an expert prior (EP) where the elicited prior location information is weighted across demand (sub) systems by experts. The degree of belief in prior information (weights) is based on its quality, which in turn has effects on accuracy and precision of the posterior estimates, and as a consequence, out of sample performance. For the empirical analysis we therefore source published PEs from two relevant and suitable studies in terms of methods and study population (Ni Mhurchu *et al*., 2013, 2015; Sharma *et al*., 2014), while the proposed weights further take into account aspects relating to the quality of published elasticities across the specific food groups. In addition, we provide all inference under uninformative default priors for comparison.

The posterior PE estimates, computed under the proposed expert as well as common uninformative priors (UIP), include point and precision estimates, as well as interval estimates with a clear probabilistic interpretation for decision-making. Including elicited prior location information via expert-based weights in the context of the moderate sample size VS data, particularly in final disaggregated food groups, we see an improvement in the precision of PE inference, as well as impacts on the magnitude of PE point estimates. The analysis yields stronger price effects, with the impact more pronounced for harder to identify cPEs with generally lower magnitudes than oPEs. Incorporating prior knowledge improves the precision of the PE estimates with standard deviations (SDs) on average 10 per cent lower for oPEs and 29 per cent lower for cPEs. Credibility intervals of 95 per cent generated using the posterior SDs exclude the null for 43 per cent of cPEs for foods within the same major group, implying complementary or substitutionary relationships. Importantly, increased PE precision can yield more reliable health gain estimates for diet interventions at the population level and more precise demand change predictions as illustrated in our analysis of policy scenarios. We simulate policy implications in terms of a 30 per cent sugar-sweetened beverages (SSB) tax on soft drinks, a 20 per cent subsidy in FV), and NZ$3 per 100 g tax on saturated fat (SAFA) finding plausible changes in related food demand with mostly clear directional changes.

Thus, the paper makes both methodological and empirical contributions. It contributes to the empirical (public) health literature by providing comprehensive PE results for a large set of disaggregated food groups, exploiting exogenous price variation in a demand experiment covering all major food groups. We expand Bayesian methods for (multi-stage) LAIDS analysis to allow the researcher to introduce suitable available prior information from published PEs. Our elicitation proposal implies prior mean parameters in the demand (sub)systems that are consistent with both theory and empirical evidence, while weighted to reflect the researchers' (experts') belief in prior information based on its quality and relevance. The approach may be less important in settings with very large sample sizes, or vague priors. However, in the context of the multi-stage analysis under the moderate sample size VS data we see an improvement in the precision of PE inference and impacts on the magnitude of PE point estimates, although higher levels of imprecision in cPE estimates with less clear conclusions remain. We show that our PE results and policy implications are broadly consistent with findings in the literature. It is important to recognize that previous studies exhibit considerable variation in estimates due to differences in data, food group definitions and methods and a focus on either highly aggregated food groups or a small set of disaggregated foods, as well as limited evidence on cPEs (Cornelsen *et al*., 2015).

II PE Analysis via the Demand System for the Virtual Supermarket Experiment

(i) Bayesian Almost Ideal Demand System (LAIDS)

We build on the LAIDS model introduced by Deaton and Muellbauer (1980), which is widely used in food demand analysis (Nghiem *et al*., 2011) given the evidence that the food Engel curves are linear (Banks *et al*., 1997). The approach ensures that the estimated substitution patterns are consistent across the different food groups: an increase in expenditure in one good must be matched by a reduction in expenditure on another good (Briggs *et al*., 2013). In addition, LAIDS satisfies the axioms of choice with homogeneity and symmetry restrictions easily imposed.

Under the standard (single-stage) LAIDS the budget share w_{ih} for shop h ($h = 1, \ldots, H$) by each food i ($i = 1, \ldots, (n+1)$) is modelled as function of a food-specific intercept α_i and log prices of all goods $\ln(p_{hj})$, and the total real expenditure $\frac{X_h}{P_h}$:

$$w_{ih} = \alpha_i + \sum_{j=1}^{n+1} \gamma_{ij} \ln(p_{hj}) + \beta_i \ln\left(\frac{X_h}{P_h}\right) + \varepsilon_{ih}, \qquad (1)$$

where α_i,γ_{ij} and β_i are parameters to estimate; X_h is the total nominal expenditure for the given household shop; and ε_{ih} is the error term such that $\varepsilon_h = [\varepsilon_{1h}, \ \varepsilon_{2h}, \ \ldots, \ \varepsilon_{nh}, \ \varepsilon_{n+1h}]' \sim N(0, \ \Sigma)$. Note that one share equation must be dropped during estimation of the demand equations to avoid perfect multicollinearity. Further, the linear price Stone index P_h is defined as:

$$\ln(P_h) = \sum_{i=1}^{n+1} w_{hi} \ln(p_{hi}). \qquad (2)$$

Arising from the microeconomic theory underlying the LAIDS model, Equation (1) is subject to the adding-up restrictions, symmetry conditions and homogeneity restrictions (see Appendix A).

Under the single-stage LAIDS, the Marshallian PE of good (food group) i with respect to the price of good j is:

$$\varepsilon_{ij} = \frac{\gamma_{ij} - \beta_i \overline{w_j}}{\overline{w_i}} - \rho_{ij}, \qquad \rho_{ij} = \begin{cases} = 1, & i = j \\ = 0, & i \neq j \end{cases}, \qquad (3)$$

where $\overline{w_j}$ is the average budget share of good j across all shops. Note that the two budget shares as well as the price coefficient γ_{ij} will appear in both the computation of ε_{ij} and ε_{ji}. The expenditure elasticity is:

$$\eta_i = 1 + \frac{\beta_i}{\overline{w}_i}. \qquad (4)$$

Under the Bayesian estimation of LAIDS, information from the data-generation process, or likelihood, is combined with the prior distribution of the model parameters to obtain estimates of the model parameters based on their posterior distribution:

$$\pi(\theta, \ \Sigma | \boldsymbol{w}) \propto \ell(\boldsymbol{w} | \theta, \ \Sigma) \ \pi(\theta, \ \Sigma), \qquad (5)$$

where vector $\theta = (\alpha, \ \beta, \ \gamma)$ contains all the demand coefficients; and Σ is the covariance of the error term. Since LAIDS is a system of linear models with a Normal error structure, efficient estimation is possible via a standard Gibbs sampler (Greenberg, 2012) using the standard conjugate choices of prior independent Normal distributions for regression coefficients and inverse Wishart for the covariance matrix (e.g., Chib & Greenberg, 1995; Kasteridis *et al*., 2011). The focus of our analysis is inference on the set of Marshallian PEs (ε) in terms of their posterior distributions:

$$\pi(\varepsilon | \boldsymbol{w}) = \int f(\beta, \ \gamma) \pi(\beta, \ \gamma | \boldsymbol{w}) d\beta d\gamma, \qquad (6)$$

which can be obtained in a straightforward manner using the formula for the PEs ($f(\beta, \ \gamma)$) and Markov chain Monte Carlo (MCMC) draws from the posterior distribution of the income and price coefficients. Hence, the posterior distribution, and thus also the prior distribution on the demand parameters, are particularly important for inference on the PEs.

Given the close link between demand parameters and PE estimates, we can exploit the Bayesian set-up to include the available information in terms of published PE estimates via the prior assumptions on the price coefficients $\pi(\gamma | \mu_\gamma, \ V_\gamma)$ and income coefficients $\pi(\beta | \mu_\beta, \ V_\beta)$. This is done via two types of prior parameters where the μ's contain location and V the diagonal covariance matrices of the demand parameter priors. The former reflects our prior beliefs about the magnitude of the coefficient and the latter reflects the strength of this belief with a large V corresponding to less weight on the prior belief. This can be considered a 'subjective empirical' Bayesian approach where informative priors are built based on previous studies to improve precision of posterior estimates due to shrinking sample and prior information (e.g., Ramírez-Hassan & Montoya-Blandón, 2020).

(ii) Multistage Demand System for Virtual Supermarket Data

Our focus is on developing a demand system to estimate the PEs for a large set of food groups from a unique recent VS experiment including all major food groups. In particular, the VS experiment created a realistic three-dimensional computer simulation of a real New Zealand (NZ) supermarket with 1,412 unique food items positioned on supermarket shelves (about 75 per cent of the products in 'real' supermarkets). VS participants were asked to complete five shopping tasks in the VS (one per week) where they were instructed to buy the groceries for their household for the coming week just as they would in real life. The experiment, run in 2016 and resulting in 4,258 completed shops, is described in detail in Waterlander *et al*. (2016, 2019), and the VS tool was validated compared with actual shopping purchases in Waterlander *et al*. (2015). Key to our PE analysis is the exogenous assignment of prices with each shop randomly allocated to a different price set without replacement. This set-up generated substantial price variation both within and across household shopping tasks.

For the PE demand analysis, we consider 23 food groups following groupings used before in NZ (Ni Mhurchu *et al*., 2013), and similar to those use across all foods in other contexts (Ministry of Agriculture, Fisheries & Food, 2000; Andreyeva *et al*., 2010), whereby foods were grouped into similar nutrient and choice categories. Of particular interest for health policy analysis are the demand cPE and oPE estimates relating to food groups such as soft drinks, F&V and (discretionary) high sugar foods. This set-up follows the previous literature on food consumption and public health pricing interventions (Tiffin & Arnoult, 2008, 2010; Briggs *et al*., 2013). Of note, we separate diet and regular soft drinks in this paper, whereas previously it had been grouped together.

A single LAIDS demand system as described in Section II(i) is typically estimated for a small number of food groups. It is poorly suited for a comprehensive demand system, spanning all major food groups, focusing on PE estimation for highly disaggregated food groups (Klonaris & Hallam, 2003). First, it is difficult to solve for such demand systems requiring the estimation of a large set of parameters, decreasing the precision of elasticity estimates; imposing a multistage structure helps to mitigate this issue. A further complication is that we observe a large amount of zero purchases in the VS data when examining all disaggregated food groupings simultaneously for each shop h. Therefore, we follow the multi-budgeting approach (Briggs *et al*., 2013; Tiffin & Arnoult, 2008, 2010; Klonaris & Hallam, 2003; Rickertsen *et al*., 2003) and consider a multistage demand system which is based on the assumption that the allocation of expenditure largely takes place in multiple independent steps. Under weak separability of preferences, such a multistage budgeting is (approximately) consistent with a complete demand analysis (Deaton & Muellbauer, 1980), assuming the linear group price indices are a good approximation of the ideal price indices.

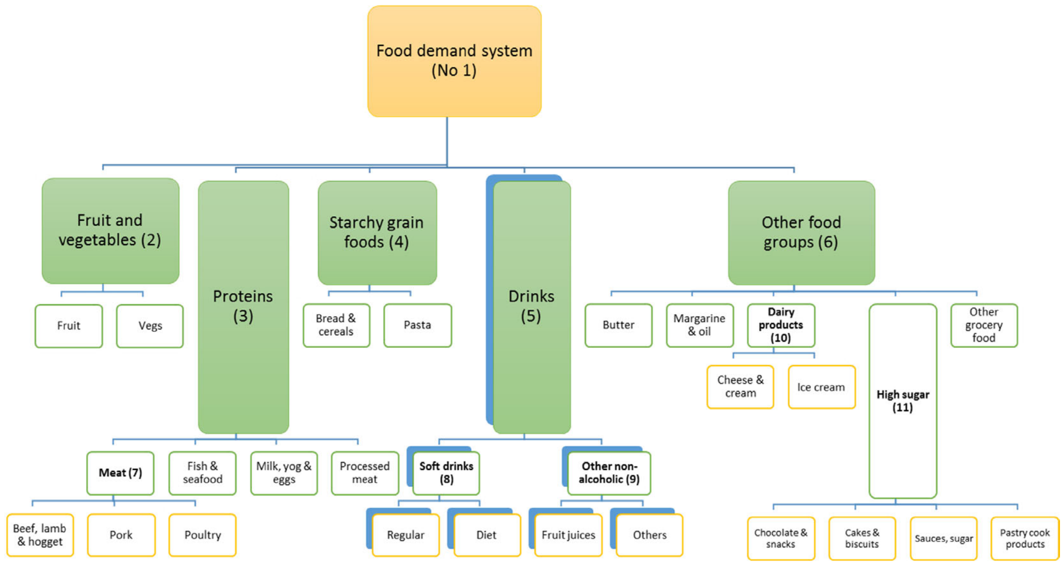
For the analysis of the VS data, we proceed in a three-level budgeting approach with 11 demand systems as defined in Figure 1. The first stage consists of the five main groups (F&V, proteins, starchy grain foods, drinks, and other), with the final stages including more disaggregated food groups such as regular soft drinks, diet soft drinks and processed meat. Within the multi-budgeting approach households move in and out of the different subsystems. Hence, a consistent modelling of a random (household) effects LAIDS model is not possible in this setting. However, given that the analysis takes place in a demand experiment with randomly assigned prices and expenditures, there are no concerns of a bias from correlation between unobserved heterogeneity and regressors.

To recover the matrix of oPEs and cPEs for a complete set of disaggregated food groups we use the Edgerton approach (Edgerton, 1997; Briggs *et al*., 2013) where price indices are computed for each demand system/grouping. Hence, the price change in a good has a direct effect on the demand of goods in the same group, holding group expenditure fixed. Such a price change further affects the allocation of expenditures between groups through the changed group price index, thus impacting all goods, both within and outside the same group. Consider a two-stage demand system, in conjunction with Equations (3) and (4), the total Marshallian (uncompensated) PEs ε_{ij} for two goods from the second stage is obtained from:

$$\varepsilon_{ij} = \rho_{rs}\tilde{\varepsilon}_{(r)ij} + \eta_{(r)i} w_{(s)j} \varepsilon_{(r)(s)} \qquad (7)$$

where r and s refer to the first stage groups associated with stage 2 goods i and j, so that $\rho_{rs} = 1$ if $s = r$ (zero if goods are in different first stage groups); $w_{(s)j}$ is the budget weight of good j in group s; $\tilde{\varepsilon}_{(r)ij} = \varepsilon_{ij} + \overline{w_j}\eta_i$ is the within-group Hicksian PE of goods i and j in the second stage; $\eta_{(r)i}$ is the within group expenditure elasticity for i in the

FIGURE 1
The 11 Food Demand Systems used in the Multistage Approach. [Colour figure can be viewed at wileyonlinelibrary.com]



Note: Stage 1 is for the entire food demand system (no. 1). Stage 2 consists of five food demand systems (Fruit and vegetables (2) to Other food groups (6)), for example, the other food groups system has five food categories within it (Butter, margarine, Dairy, High sugar, and Other grocery food). Stage 3 consists of five food demand systems (Meat (7), Soft drinks (8), Other non-alcoholic (9), Dairy products (10) and High sugar (11)).

second stage; and $\varepsilon_{(r)(s)}$ the first stage Marshallian PEs for groups r and s. Note that this implies that cPEs for foods in the same second stage are the results of a direct effect (the first component in Eqn 7) as well as an indirect effect from the allocation of expenditures between groups through a change in the group price index, thus impacting demand for all goods (the second component in Eqn 7). Hence, for foods that are part of different stage 1 groups, cPE effects are based on the indirect effect only. This implies *ceteris paribus* small cross-PEs for goods that are separated far away in a multistage budg*et al*location framework. For more details, see Appendix A.

(iii) Additional PE Information via Priors on Demand Parameters

Of particular interest in our context are the prior distributions for γ and β as these parameters determine the price and expenditure elasticity estimates. Proceeding with the standard choice of independent priors from the Normal family for demand parameters, the prior is:

$$\pi(\theta) = \mathrm{N}(\theta|\mu_0,\ V_0) = \mathrm{N}(\alpha|\mu_\alpha,\ V_\alpha) \times \mathrm{N}(\gamma|\mu_\gamma,\ V_\gamma) \times \mathrm{N}(\beta|\mu_\beta,\ V_\beta),$$

where the μ's reflect the location; and V's the diagonal covariance matrices of the demand parameters. We set the most relevant prior means, μ_γ and μ_β, in a combination of a predictive and structural prior elicitation approach discussed below (Ramírez-Hassan & Pericchi, 2018) using additional information available from previous PE studies.

The starting point to specify the additional information via the prior means of the price and expenditure parameters, μ_γ and μ_β, is the 'published PE matrix' from previous studies rather than the demand parameters, as very few studies have actually published demand coefficients (and their

SDs). In our empirical analysis we consider PEs from a previous NZ study for all foods (Ni Mhurchu *et al*., 2013, 2015) (the SPEND study), and an Australian study (Sharma *et al*., 2014) for diet and regular soft drinks which were not provided disaggregated in the NZ study. SPEND is the most comprehensive study that proceeds with a similar demand analysis and in a comparable setting in terms of a representative sample of the NZ population, while the second study is the closest available proxy in terms of the target population and demand analysis that reports diet and soft drink PEs. The strength of the additional information provided in terms of the elicited prior means μ_γ and μ_β is controlled by the dispersion of the prior variance around its mean. Here we consider a diagonal prior variance of the form $V_0 = sI$ in each demand system, where I is an identity matrix; and s is a scaling factor determined by the researchers (expert) and as discussed further in Section III(ii).

Below we outline a procedure to convert available published PE information into information on the demand parameters to address three complications that arise in this elicitation process. First, the published PEs refer to final good groupings but not to more aggregated levels required at earlier stages in a multistage estimation system. Second, we need to ensure the PE matrix for each demand system is consistent with microeconomic conditions since PEs from the literature do not automatically satisfy demand restrictions when converted back to demand coefficients using different demand structures or budget shares. And third, there is no simple one-to-one relationship between PEs and demand parameters as evident from Equation (3). As the prior elasticities are given at a disaggregated level, the first step in our proposed approach is to take into account the aggregation of these elasticities where required, that is, in each of the demand systems containing aggregated goods. For instance, we need to aggregate a 23 × 23 prior PE matrix into a 5 × 5 matrix for the first stage in our system. We weighted prior elasticities by its budget shares to perform this aggregation:

$$\varepsilon_{ij}^{G_l} = \frac{\sum_{i,j\in G_l} w_{i\in G_l}^{Prior} \varepsilon_{ij}^{Prior}}{\sum_{i\in G_l} w_{i\in G_l}^{Prior}}, \tag{8}$$

$$\eta_i^{G_l} = \frac{\sum_{i\in G_l} w_{i\in G_l}^{Prior} \eta_i^{Prior}}{\sum_{i\in G_l} w_{i\in G_l}^{Prior}}, \tag{9}$$

where $\varepsilon_{ij}^{G_l}$ and $\eta_i^{G_l}$ are the prior aggregated price and expenditure elasticities for system G_l, $l = 1, 2, \ldots, 11$; and $w_{i\in G_l}^{Prior}$ is the budget share of good i in group G_l from the disaggregated previous studies, and ε_{ij}^{Prior} and η_i^{Prior} prior disaggregated prior elasticities.

Next, optimisation procedures are used to generate a microeconomic consistent PE matrix (taking into account adding-up and homogeneity restrictions; see Appendix A) for each food demand system and to convert these PE matrices into prior means on the coefficients in the demand equations. We obtain the mean hyperparameters solving the following program:

$$minf\left(\varepsilon_{ii}^{Opt},\ \eta_i^{Opt}\right) = \sum_{i=1}^{nfood} \left(\varepsilon_{ii}^{Opt} - \varepsilon_{ii}^{G_l}\right)^2 + \left(\eta_i^{Opt} - \eta_i^{G_l}\right)^2 \tag{10}$$

for the optimal prior elasticities, which are converted into hyperparameters using LAIDS microeconomic restrictions. In order to find a set of parameters that simultaneously satisfy all restrictions, we impose lower and upper bounds for the elasticities. We focus on matching the (aggregated) oPEs, which are the main drivers of demand, as closely as possible while bounds on cPEs are set more based on knowledge about cPE ranges in the literature. Appendix B provides more detail on the implementation of the optimisation procedure.

Tables B2 and B3 in the Appendix B are examples of Marshallian PEs for the first-stage food group before and after the optimisation process. Other prior PEs matrices are available from the authors upon request.

III Empirical Analysis

(i) Virtual Supermarket Sample

In total, the VS experiment randomised 1,132 participants (households) who were invited to complete five shops. A total of 1,037 households (91.6 per cent) completed at least one shop, while 744 (65.7 per cent) completed all five shops. In total, we observe $n = 4{,}258$ completed shops (Waterlander *et al*., 2019), which form the sample for our analysis. The household VS budget was set between 50 per cent and 125 per cent of their estimated average household shopping budget reported before their first shop. The mean age of VS shoppers was 32.9 years with an average household size of three people. Female participants accounted for 79.2 per cent. Indigenous Māori participants and NZ Europeans contributed 11.4 per cent and 71.3 per cent of the total participants, respectively. Compared with the NZ demographic Census 2013, the ethnicity and household size were similar.

Table 1 shows the VS data disaggregated by the 11 food systems shown in Figure 1 and used in the subsequent multistage LAIDS analysis. At the highest level, or stage 1, there were 2,744 shops with non-zero data in all the five food groupings used at stage 1, with budget shares of: 33 per cent for proteins food groups, 23 per cent for F&V, 11 per cent for starchy and grain products, 8 per for cent drinks, and the remaining 25 per cent for 'other' food groups. The number of shops with non-zero shops in all foods within each demand system ranged from 122 for 'other' foods (i.e., non-zero consumption of each of butter, high-sugar, dairy, margarine and edible oils and 'other' groceries) to 3,942 for F&V. Average expenditure ranged from NZ$5.55 for diet soft drinks (restricted to those shops with non-zero purchasing of both diet and regular soft drinks) to NZ$58.34 for proteins.

(ii) Expert Prior Specification

The multistage demand analysis of the VS data proceeds via the Bayesian approach to estimate the 11 demand systems and PEs for all 23 good groups. A key feature is the inclusion of available PE information via prior demand parameter means and corresponding weights (prior variances) set with the help of a team of four public health experts in the area, including two authors of the paper. As already described in Section II (iii), the prior location parameter for the demand parameters in each demand system is elicited based on published PE estimates of two suitable studies. Tables 2–4 present the associated optimised prior Marshallian PEs for three of the final demand systems. The prior oPEs are mostly elastic and overall somewhat higher in absolute terms than the majority of the oPEs in the literature as well (Nghiem *et al*., 2013). However, except for pork with an oPE (SPEND) of around −3, the remaining prior oPEs where in the range reported in the literature, including the 'lowest' oPE obtained for the fruits group of around −0.5 which is comparable with the results in Thiele (2010).

The prior specification is concluded by the setting of the prior variances on all demand parameters in terms of demand system-specific scaling parameters. The aim is to weigh the prior information relative to the data while also adjusting for the variation in the quality of the sample and prior information across different food groups, as well as taking into account substantial differences in sample sizes across demand systems as reported above. Specifically, for each demand system a set of scale/variance parameters was obtained by solving an optimisation program to reflect different weights between prior information and the data of either 25 per cent (scaling towards data), 50 per cent (equal weight) or 75 per cent (scaling towards prior). These weights were computed based on the average distance between prior oPEs and data-only based estimates given their larger magnitudes than cPEs and prominence in the public health literature. Next, for each demand system a weight was chosen in accordance with the expert judgement of public health experts, including two authors of the paper as well as two external researchers, reflecting whether the VS type data representing a supermarket setting was a better reflection of the real-world choice of consumers or too limited, excluding convenience and other purchase points that were included in the data underlying the SPEND study (see Appendix B for more details). Table B1 in the Appendix B reports the scaling factors for all systems, implied weights and expert considerations that supported the specific weight choice. For example, the scaling in the meat system was towards VS data taking into account that meat is most commonly purchased in supermarkets (while SPEND covered a wider range of stores). The corresponding scale factor takes the value of 0.001.

We want to stress that while the weights under the expert specification imply different strength informative priors across subsystems, they will not restrict the support of the posterior distribution of the demand parameters, that is, the possible range of demand parameters and PE estimates.

(iii) Price Elasticity Results

As described in Section II, we estimate 11 demand systems based on the LAIDS model specified in Equations (1) and (2) for the VS data under the EP, based on which the PE estimates of the final food groups are computed using the Edgerton approach. Exemplar 'results' from the model estimation are shown in Tables S1–S3. For the remainder of this section, though, we focus on

Table 1
Descriptive Statistics for VS Data Disaggregated by the 11 Demand Models

Demand model number	Food groupings (corresponding to Fig. 1)	N with non-zero consumption in all food groups in demand model	Quantity (kg) per shop	Expenditure (NZ$)	Budget share
Overall	Fruit and vegetables	2,744	6.64 (4.41)	NZ$39.81 (24.74)	0.23 (0.11)
	Proteins		6.50 (3.85)	NZ$58.43 (38.62)	0.33 (0.12)
	Starchy grains		3.19 (2.31)	NZ$19.17 (13.27)	0.11 (0.06)
	Drinks		1.95 (2.36)	NZ$12.27 (9.12)	0.08 (0.05)
	Other food groups		3.57 (2.42)	NZ$44.59 (28.21)	0.25 (0.10)
Fruit and vegetables	**Fruit**	3,942	2.25 (1.87)	NZ$12.39 (10.51)	0.32 (0.17)
	Vegetables		4.20 (3.19)	NZ$26.66 (17.89)	0.68 (0.17)
Proteins	**Fish and seafood**	1,147	0.64 (0.47)	NZ$14.14 (12.89)	0.18 (0.12)
	Meat		1.96 (1.40)	NZ$37.16 (27.42)	0.43 (0.16)
	Milk, yoghurt and eggs		4.64 (2.84)	NZ$16.69 (10.00)	0.22 (0.11)
	Prepared and processed meat		0.78 (0.56)	NZ$11.96 (7.67)	0.16 (0.09)
Starchy grain products	**Bread and breakfast cereals**	2,429	2.13 (1.43)	NZ$14.33 (9.86)	0.64 (0.19)
	Pasta and other cereal products		1.61 (1.32)	NZ$7.57 (6.36)	0.36 (0.19)
Drinks	Carbonated soft drinks	749	2.76 (1.94)	NZ$6.33 (4.58)	0.37 (0.19)
	Other non-alcoholic beverages		1.42 (1.75)	NZ$11.88 (8.91)	0.63 (0.19)
'Other food groups'	**Butter**	122	0.61 (0.26)	NZ$7.02 (4.26)	0.10 (0.05)
	High sugar food groups		2.76 (1.85)	NZ$35.96 (21.22)	0.43 (0.17)
	Dairy		1.90 (1.41)	NZ$22.04 (16.59)	0.27 (0.13)
	Margarine and edible oils		0.88 (0.52)	NZ$7.88 (5.48)	0.11 (0.09)
	Other grocery foods		0.79 (0.68)	NZ$7.43 (6.06)	0.10 (0.06)
Meat	**Beef, lamb and hogget**	1,089	1.03 (0.68)	NZ$21.66 (16.05)	0.43 (0.16)
	Pork		0.62 (0.58)	NZ$12.20 (11.51)	0.25 (0.14)
	Poultry		0.94 (0.65)	NZ$14.88 (9.93)	0.32 (0.14)
Soft drinks	**Diet soft drinks**	124	2.49 (2.12)	NZ$5.55 (4.93)	0.48 (0.18)
	Regular soft drinks		2.10 (1.35)	NZ$5.75 (3.54)	0.52 (0.18)
Other non-alcoholic drinks	**Fruit drinks and fruit juice**	530	2.21 (1.37)	NZ$6.79 (3.64)	0.43 (0.17)
	Other non-alcoholic drinks		0.62 (1.23)	NZ$10.45 (7.65)	0.57 (0.17)
Dairy products	**Cheese and cream**	726	0.91 (0.60)	NZ$15.65 (10.60)	0.62 (0.15)
	Ice cream		1.51 (0.90)	NZ$7.96 (3.61)	0.38 (0.15)
High sugar	**Cakes and biscuits**	316	0.75 (0.60)	NZ$11.00 (8.55)	0.23 (0.12)
	Chocolate and confectionary		0.67 (0.49)	NZ$12.92 (10.26)	0.26 (0.13)
	Pastry cook products		0.64 (0.54)	NZ$7.76 (4.79)	0.18 (0.09)
	Sauces and sugar condiments		1.45 (1.10)	NZ$15.74 (10.93)	0.33 (0.16)

Note: Food items used in the final price elasticities matrix (most disaggregated food groups) are shown in bold. Values in parentheses refer to standard deviations.

TABLE 2
Optimised Prior Marshallian Price Elasticities System 8 (Soft Drinks)

	Diet soft drinks	Regular soft drinks
Diet soft drinks	−1.01	−0.40
Regular soft drinks	0.01	−0.63

Note: Estimates are optimised (i.e., recalculated so that demand coefficients satisfied microeconomics restrictions) based on price elasticities extracted from Sharma *et al*. (2014).

the PE estimates for the 23 final food groups with key PE estimates presented in Tables 5–7. They report the posterior mean estimates and SDs of all Marshallian oPEs (in italics), as well as cPEs across food groups belonging to the same second- and third-stage systems (bold blocks), that is, the same major food group.

A total of 12 out of the 23 food group demands were responsive or elastic to price changes, that is, absolute values of oPEs > 1. Of the remaining, there were eight inelastic groups and three unitary elastic groups (using one decimal). The least price responsive food group was butter (Ope = −0.31), and the most elastic one was 'other groceries' (all the remaining foods in the VS that did not match any of the food groups listed in Figure 1, oPE = −2.62), although both were estimated with low precision due to sparse data. Soft drinks demand was inelastic, with oPEs being −0.62 and −0.77 for diet and regular soft drinks, respectively, but precisely estimated with SDs < 0.1. These results are in line with several recent studies that have estimated PEs relating to soft drinks with a mean oPE of −0.79 across 14 studies reported by Andreyeva *et al*. (2010), but lower than the high elasticity results in other recent work with scanner data in the US context (Allcott *et al*., 2019; Valizadeh & Ng, 2021). The estimated PEs for F&V, and cheese, cream and milk and yoghurt and eggs, on the other hand, were either close to or >1 in absolute terms ranging between −0.93 and −1.52. These were higher than the oPEs reported for associated higher aggregated groups in Cornelsen *et al*. (2015), but close to the oPEs in Kehlbacher *et al*. (2020) for F&V from UK data, and the median oPEs reported in Zhen *et al*. (2014) for milk, yoghurt and cheese in US home scanner data. For meats (beef/lamb, port, poultry) our expert PE estimates ranged between −0.63 and −1.02. For processed meats we estimated an oPE of −1.06. These values are consistent with the oPE estimates close to −1 for the aggregate meat group in Kehlbacher *et al*. (2020). While a meta-analysis for more aggregated food groups has predicted positive oPEs for meat and fish for some high-income countries (Cornelsen *et al*., 2015), generally oPEs in that study were between 0 and −1.0 (i.e., inelastic). Also, an earlier meta-study focusing on meat oPEs across countries reported a median oPE of −0.71 and oPEs between −0.65 and −0.94 for the more disaggregated meat and the fish groups similar to the ones considered in our analysis (Gallet, 2010). A research report on Australian meat demand elasticities (Griffith *et al*., 2001) that surveyed a large number of studies up to the year 2000 overwhelmingly shows negative oPEs for beef, lamb, pork and poultry, with the majority of reported retail demand elasticities around or above −1 (close to or high elasticity).

Tables 5–7 also report the cPEs for food groups belonging to the same second stage (the values in normal font) and third-stage systems (the values in bold font). The cPEs within the big food groups drinks, F&V, proteins, starchy foods and other, as well as within the more disaggregated food groups soft drinks, other non-alcoholic, dairy products, meats, high sugar products (the values in bold font in Tables 5 and 6) were often moderate within food groups. Specifically, of the 118 filled in cells in Tables 5–7 for cPEs (i.e., off diagonal), 22 per cent had an absolute value > 0.1, 21 per cent between 0.05 and 0.1, and 40 per cent between 0.01 and 0.05. Note that within a multistage LAIDS model we expect very small cPEs for food groups belonging to different major food groups as the model assumption implies that expenditure across the big five good groups is fixed (weak separability assumption underlying multistage budgeting model). This is reflected in very small cPEs estimates, with average absolute values of cPEs in the empty cells being 0.0025 and often < 0.01 (see Tables

Table 3

Optimised Prior Marshallian Price Elasticities System 11 (High Sugar)

	Cakes and biscuits	Chocolate confectionary	Pastry products	Sauces and sugar condiments
Cakes and biscuits	−0.97	−0.05	0.09	0.02
Chocolate confectionary	−0.08	−1.27	0.13	0.16
Pastry products	0.13	0.25	−1.52	0.31
Sauces and sugar condiments	−0.03	0.12	0.12	−1.32

Note: Estimates are optimised (i.e., recalculated so that demand coefficients satisfied microeconomics restrictions) based on price elasticities extracted from Ni Mhurchu *et al.* (2013).

S4 and S5 with complete set of posterior means and SDs).

Overall, the reported cPE estimates are mostly one order of magnitude lower in absolute value than the oPEs. These patterns are consistent with theory and limited available empirical evidence, in particular for disaggregated food groups, which reports small cPEs such as Briggs *et al.* (2013) and Zhen *et al.* (2014), and to a somewhat lesser degree Allcott *et al.* (2019) and Valizadeh and Ng (2021). Note that these studies only contain a subset of (similar) food groups considered in our analysis, as existing work in health has focused on either highly aggregated food groups or a small set of disaggregated foods, in addition to a focus on oPEs (Cornelsen *et al.*, 2015). Regarding the fruits and drinks groups, we find weak evidence for a substitution from F&V similar in size to the effect reported in Thiele (2010) from a LAIDS analysis of German survey data, but we also find a much stronger effect in the other direction. Turning now to the soft drink system, the positive estimate between diet drinks and soft drinks, that is, diet drinks are complements to soft drinks, are consistent with the positive effects reported in Allcott *et al.* (2019) and Zhen *et al.* (2014), although lower in magnitude. For diet drinks, Zhen *et al.* (2014) find some evidence for a complementary relationship with soft drinks, in particular energy drinks, compared with a small negative effect in the VS analysis under EP. The cPE estimates across the three meat groups lie in the range of estimates in the survey paper by Griffith *et al.* (2001), although that paper only reported a subset of cPEs and considered four meat groups (beef, lamb, pork and poultry). The two significant cPE relationships we find in the meat demand system are complementary relationships between beef/lamb and poultry and vice versa with point estimates of –0.262 (SD = 0.04) and –0.349 (SD = 0.06). The former is consistent with the cPEs for beef and poultry in the most recent studies in the survey paper, while the evidence on the latter is less clear.

Regarding precision estimates, as pointed out in Cornelsen *et al.* (2015), many studies do not report precision for PE estimates as these are often difficult to obtain under frequentist analysis in a multistage setting (Ramírez, 2013). Within our multistage Bayesian framework, precision information based on the SDs is computed based on the posterior simulation draws of the elasticities. Hence, the SDs refer

TABLE 4
Optimised Prior Marshallian Price Elasticities System 7 (Meat)

	Beef, lamb and hogget	Pork	Poultry
Beef, lamb and hogget	−1.20	0.65	−0.00
Pork	0.65	–2.97	0.65
Poultry	−0.24	0.65	−1.51

Note: Estimates are optimised (i.e., recalculated so that demand coefficients satisfied microeconomics restrictions) based on price elasticities extracted from Ni Mhurchu *et al*. (2013).

TABLE 5
Price Elasticities Estimates for Drinks and Fruit and Vegetables

Final food group	1	2	3	4	5	6
Diet soft drinks	***−0.627***	**0.063**	*0.054*	*0.072*		
	(0.049)	**(0.053)**	*(0.010)*	*(0.014)*		
Regular soft drinks	**−0.082**	***−0.774***	*0.083*	*0.109*		
	(0.047)	**(0.051)**	*(0.016)*	*(0.021)*		
Fruit drinks and juices	*−0.056*	−0.061	***−1.025***	**0.240**		
	(0.006)	(0.007)	**(0.045)**	**(0.035)**		
Other non-alcoholic	−0.093	−0.102	**−0.045**	***−1.266***		
	(0.010)	(0.011)	**(0.022)**	**(0.045)**		
Fruit					***−0.928***	**−0.032**
					(0.030)	**(0.015)**
Vegetables					**−0.139**	***−1.542***
					(0.012)	**(0.039)**

Note: Estimates are based on the posterior means; standard deviations are shown in parentheses. PE estimates for 2nd and 3rd stage systems. Bold value results refer to PEs for foods in the same 3rd stage system. Own price elasticities are in italics.

to the spread or dispersion of the posterior distributions and therefore directly reflect our uncertainty about an elasticity parameter given the observed data and prior information. In 43.5 per cent of the cases the absolute values of the cPE estimates are less than two times the posterior SD. While we show in the next section that the analysis under additional information via the EP has improved the overall precision in the PE estimation, a considerable proportion of cPE estimates with large SDs remains, a finding consistent with the general challenge of identifying substitution effects across disaggregated food groups already highlighted in previous studies (Jevdjevic *et al*., 2019). Given current public health interest in taxes of regular soft drinks, and the expectation that diet soft drinks would be a substitute, we note that the cPE of regular onto diet soft drinks was in the expected direction at 0.063 (albeit with a SD nearly as large at 0.053) (Table 5).

(iv) Comparison with Uninformative Priors

Next, we explore how the use of prior information affected the PE inference in the VS sample by repeating the analysis with UIP. For this analysis we use large scaling factors that reflect a strong scaling towards the data, hence the results are comparable with a frequentist analysis without prior information. Recall that one motivation for using a Bayesian approach in this context was to reduce the high imprecision common in PE estimation (i.e., larger SDs), especially for more disaggregated food groups, through EP based on previous study results. Posterior mean and SDs for all elasticities under both priors are reported in Tables S4–S8 and differences in absolute magnitude in Table S9. Comparing precision of estimates, SDs for the posterior oPE estimates were 10 per cent less (on average over the 23 oPE estimates) than SDs for PEs generated with strong scaling toward the data (reflecting UIP). Similarly, the SDs were 29 per

TABLE 6
Price Elasticities Estimates for Other Food Group

Final food group	7	8	9	10	11	12	13	14	15
Butter	***−0.306***	0.025	0.015	0.008	0.010	0.007	0.012	−0.104	−0.212
	(0.392)	(0.060)	(0.036)	(0.030)	(0.034)	(0.023)	(0.042)	(0.122)	(0.220)
Cheese cream	−0.021	***−1.077***	**0.059**	0.013	0.015	0.010	0.018	−0.071	0.022
	(0.057)	**(0.059)**	**(0.041)**	(0.020)	(0.023)	(0.015)	(0.028)	(0.066)	(0.110)
Ice cream	**−0.022**	**0.067**	***−1.134***	0.013	0.015	0.010	0.019	−0.075	0.023
	(0.060)	**(0.066)**	**(0.052)**	(0.021)	(0.024)	(0.016)	(0.029)	(0.070)	(0.116)
Cakes and biscuits	−0.034	0.009	0.005	***−1.007***	**−0.073**	**0.039**	**−0.088**	0.000	0.148
	(0.044)	(0.030)	(0.018)	**(0.043)**	**(0.043)**	**(0.036)**	**(0.068)**	(0.049)	(0.085)
Chocolate confectionary	−0.036	0.009	0.006	**−0.080**	***−1.249***	**0.083**	**0.046**	0.000	0.157
	(0.047)	(0.032)	(0.019)	**(0.038)**	**(0.042)**	**(0.033)**	**(0.062)**	(0.052)	(0.091)
Pastry cook products	−0.029	0.008	0.005	**0.086**	**0.183**	***−1.383***	**0.144**	0.000	0.127
	(0.038)	(0.026)	(0.016)	**(0.045)**	**(0.047)**	**(0.044)**	**(0.071)**	(0.042)	(0.073)
Sauces and sugar condiments	−0.048	0.012	0.007	**−0.165**	**−0.063**	**−0.030**	***−1.321***	0.000	0.206
	(0.061)	(0.042)	(0.025)	**(0.050)**	**(0.053)**	**(0.042)**	**(0.097)**	(0.069)	(0.119)
Margarine edible oil	−0.098	−0.025	−0.015	0.031	0.036	0.025	0.044	*−0.565*	−0.175
	(0.111)	(0.066)	(0.040)	(0.032)	(0.037)	(0.025)	(0.045)	**(0.411)**	(0.208)
Other grocery food	−0.467	0.021	0.013	0.199	0.229	0.157	0.283	−0.438	*−2.622*
	(0.405)	(0.236)	(0.142)	(0.126)	(0.145)	(0.099)	(0.179)	(0.443)	(1.817)

Note: Estimates are based on the posterior means; standard deviations are shown in parentheses. PE estimates for 2nd and 3rd stage systems. Bold value results refer to PEs for foods in the same 3rd stage system. Own price elasticities are in italics

Table 7
Price Elasticities Estimates for Proteins and Starchy Grain foods

Final food	16	17	18	19	20	21	22	23
Fish seafood	*−0.885*	0.017	0.010	0.013	−0.114	−0.244		
	(0.082)	(0.019)	(0.011)	(0.014)	(0.029)	(0.037)		
Beef, lamb and hogget	−0.031	***−0.847***	**0.034**	**−0.262**	−0.020	0.002		
	(0.019)	**(0.045)**	**(0.031)**	**(0.041)**	(0.019)	(0.030)		
Pork	−0.029	**0.091**	***−1.017***	**−0.078**	−0.019	0.002		
	(0.018)	**(0.055)**	**(0.058)**	**(0.055)**	(0.018)	(0.028)		
Poultry	−0.031	**−0.349**	**−0.074**	***−0.635***	−0.020	0.002		
	(0.019)	**(0.057)**	**(0.042)**	**(0.070)**	(0.019)	(0.029)		
Milk, yoghurt and eggs	−0.095	0.030	0.017	0.022	***−1.418***	−0.044		
	(0.023)	(0.015)	(0.009)	(0.011)	**(0.066)**	(0.028)		
Prepared processed meat	−0.246	0.055	0.031	0.040	−0.044	***−1.061***		
	(0.037)	(0.029)	(0.017)	(0.021)	(0.035)	**(0.181)**		
Bread and breakfast cereals							*−1.316*	−0.058
							(0.074)	(0.022)
Pasta and other cereal							−0.114	*−1.274*
							(0.041)	**(0.067)**

Note: Estimates are based on the posterior means; standard deviations are shown in parentheses. PE estimates for 2nd and 3rd stage systems. Bold value results refer to PEs for foods in the same 3rd stage system. Own price elasticities are in italics.

cent less on average for the main cPEs within food groups (values in italics in Tables 5–7). The improvement in the precision is also clearly visible in Figures 2 and 3 which show the bar plots for the oPE and cPE estimates under the EP alongside the results for the UIP. While Figure 3 shows a clearly visible reduction in the 95 per cent credibility intervals for more than half of the 28 cPEs and only one cPE more precisely estimated under the UIP, in Figure 2 we can observe an increase in the precision for about one-third of the 23 oPEs. With theory implying gains in precision of model parameter estimates, this does not necessarily translate into gains in all PE estimates. As these are functions of parameters and budget shares, their precision also depends on the covariance between posterior parameter estimates.

Figures 2 and 3 also show changes in point and interval estimates for oPE and cPE inference. For four out of 22 oPEs (food groups 4, 12, 13 and 20), moving to EP yields a significant result due to the increased precision and in some cases changes in point estimates. In four oPEs (foods 5, 9, 11 ad 23) there is a significant change in the level of elasticity (three are highly elastic under EP). In a further five cases (foods 6, 9 and 16–18) we see a significant change in magnitudes, but no change in elasticity conclusions. Given the more difficult identification of cPEs, in nine (four) cases we observed overlapping intervals that include zero (do not include zero) under the two priors, as well as nine cases with changes in significance moving to EP estimates. The latter includes significant complementary effects becoming insignificant, as well as significant substitutionary effects emerging. These changes are mostly a result of an increase in precision, often combined with a change in point estimates towards the prior value, which typically lies outside the uninformative interval estimate and is also outside the expert interval estimate.

Broadly speaking, the observed patterns encompass what we would expect as the posterior mean in the EP is a weighted average between sample means (UIP analysis) and prior means (elicited PEs), with the uninformative mean converging to the General Least Squares (GLS) estimator. In particular, in the context of the moderate sample sizes for the disaggregated demand system analysis, including samples below 500 for systems 6 (‘other food groups’ – including high fat and sugar groups), 8 (soft drinks) and 11 (high sugar), prior information can impact precision as well as point estimates as seen, for example, in demand system 11 (foods 10–13). Hence, confidence in the posterior estimates under the EP versus non-informative prior will depend on the confidence in the elicitation process and the specific sample.

Recall that our prior oPEs are mostly elastic. Hence, Figure 2 shows a stronger price response under the expert (informative) prior indicated by a number of PE estimates (10 out of 23) moving below the line at –1 and no overlap in the 95 per cent credibility intervals in about 25 per cent of the food groups. These changes affect both healthy and unhealthy (high sugar/fat) foods as summarised in Table 8, which reports non-overlapping interval estimates for oPEs under both priors. Under the EP, several food groups become highly elastic, including non-alcoholic drinks, high-sugar groups such as ice cream and chocolate confectionary, as well as pork (meat group) and pasta and cereals (starchy group) with higher prior oPEs compared with non-informative estimates and small sample sizes. Fruits on the other hand are now inelastic, meaning a smaller percentage decrease in demand relative to a percentage change expenditure, as this was one of the few groups with a low prior oPE. Note that soft drinks, a major target of food price interventions via a sugar tax, remain inelastic under both priors. System 9 (other non-alcoholic drinks) is another example where the EP has no impact on oPE inference. Overall, and reflecting the complexity of the prior-posterior relationships, changes in elasticities as reported in Table 8 are observed across systems with different weights and sample sizes.

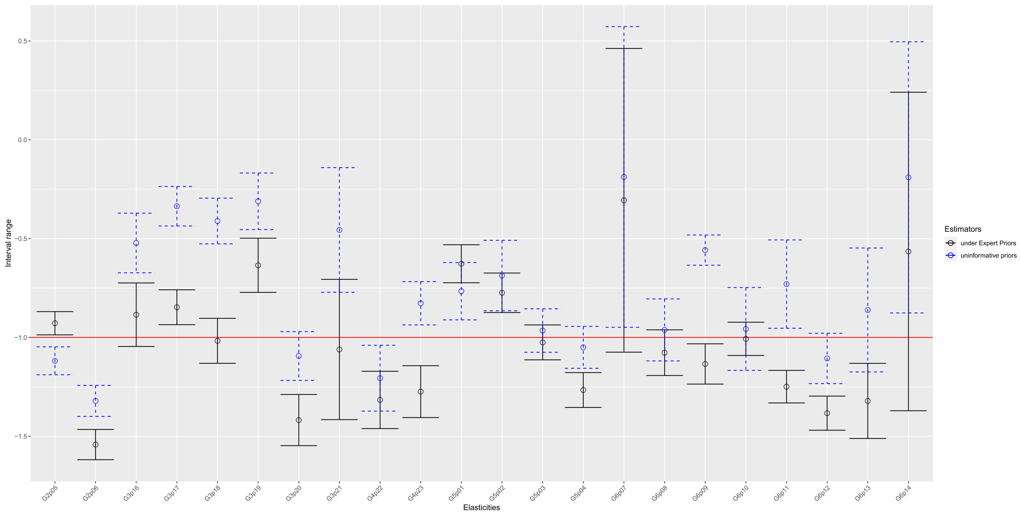
The comparison between prior and expert PEs further highlights that the conclusions do not always agree with the EP (when the former disagree with the non-informative estimates) as the posterior inference combines information from the prior and the data (via the likelihood). Hence, in case of strong information in the data that is different from the prior (such as beef, poultry or vegetables) we still find non-elastic oPEs under the EP. Note that prior elicitation defines location model parameters rather than elasticities, with the latter functions of the parameters and shares. Hence, in some cases we may observe patterns where inference under EP does not move towards the prior, as in the case of vegetables or diet drinks.

Turning to Figure 3 for cPEs, we notice a generally higher imprecision in the estimate, with considerable overlap in the 95 per cent posterior intervals for 18 out of 28 cPEs and a large proportion of the intervals including zero. This includes cases with strong information from the sample such as the cPE for beef/pork, beef/poultry and pork/poultry where the prior does not agree with the uninformative estimate in terms of type of relationship (substitutionary or complementary). Recall that our focus is on cPEs within the same final stage given the analysis being based on the multistage budgeting approach (only indirect effects can drive substitution/complement for goods in different final stage systems within such a framework). For cPEs, important changes in estimates are sign changes in the estimates. As Figure 3 reveals, a number of these cPEs move across the zero-line, including estimates for high fat/sugar food groups and drinks groups of particular interest for policy. Focusing on cPE point estimates, moving to an EP we observe most changes from (significant) complimentary effects towards substitutes (mostly insignificant positive expert cPEs) in settings with positive prior cPEs across several demand systems, including high sugar foods and meats, as well as soft drinks. In over 50 per cent of cases, the prior cPE is of the same sign and/or in the interval of the non-informative estimate. And in several cases the strong complementary priors only yield insignificant and weak complementary effects due to strong signals from the data as in the relationship between beef and pork (and vice versa). Although most 95 per cent credibility intervals contain zero due to the general challenge of precisely identifying cPEs, one can argue that coefficient sign changes are relevant to policy design (with a large proportion of posterior interval over the correspondingly signed support). Table 9 reports interval estimates for food groups where the intervals under both priors are not overlapping. In most cases the complementary relationship under the UPI is becoming insignificant as mentioned above, with this pattern observed across different systems (dairy, high sugar, and meat) with subsamples ranging from 316 to 3,942 and different scaling factors. For example, scaling was towards the data in the meat system, towards the prior in the high sugar system, and equally between data and prior in the dairy system.

(v) Policy Implications

Less than ideal nutrition contributes to large health losses globally – be it through obesity and overweight or dietary risk factors such as SAFA, salt and sugar (Stanaway *et al*., 2018). Unfortunately, individualised interventions, such as dieting, usually have modest impacts at best (Nghiem *et al*., 2015; Cleghorn *et al*., 2019). Structural interventions, such as pricing may have greater

Figure 2
Posterior Means and 95 per cent Credibility Intervals for Own Price Elasticities (oPEs) under Expert Priors and Uninformative Priors. [Colour figure can be viewed at wileyonlinelibrary.com]



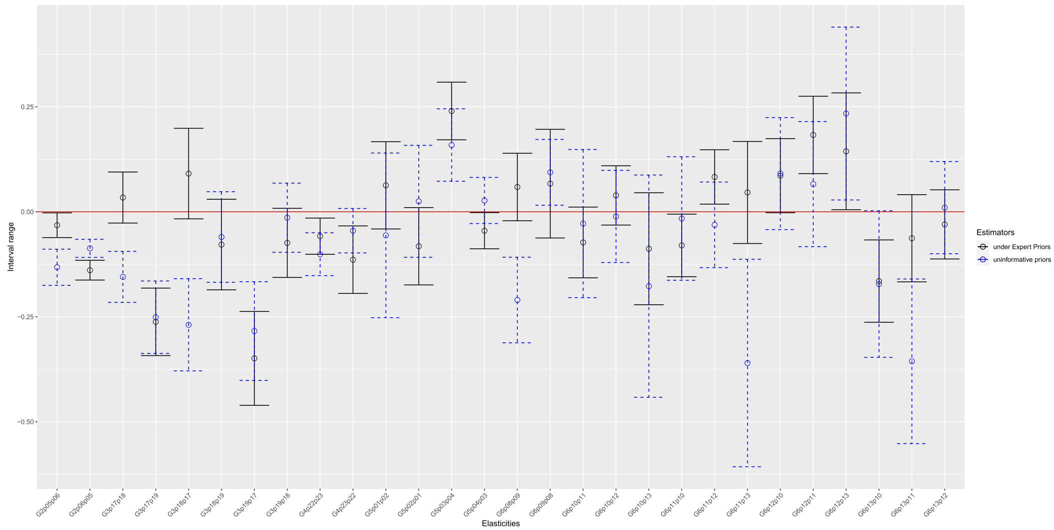
Note: Results are reported for the final stage systems. Food group Other grocery food (p15) was excluded; see Tables 5–7 for food group codings. 'G#' indicates the group of the good; and 'p#' indicates the number of the item (see Figure 1).

potential to improve diets and have gained in prominence with the World Health Organization's (WHO) Food and Nutrition Action Plan calling for rigorous action through a whole-of-government, health-in-all-policies approach with a focus on improving food environments, including via targeted food taxes and subsidies (WHO, 2015; Colchero *et al*., 2016; Duckett *et al*., 2016; Cobiac *et al*., 2017). Both, own price effects and complementary (substitutionary) effects are essential when designing and assessing such price-based dietary interventions.

First, we take a closer look at the magnitudes to the estimated PEs under the EP, in particular with respect to the strength of the price responses. Starting with oPEs, Figure 2 reveals that out of the 23 final good groups, nine clearly exhibit high elasticities with estimates below –1 and the 95 per cent credibility interval range values also below –1. Interpreting the results with respect to health gains from price interventions, we observe that all high sugar non-drink products are elastic (group 6 items), while the picture is more mixed for drinks (group 5), including soft drinks, and high-fat products (spread across different groups). Further, other non-alcoholic drinks are highly elastic as well as milk/yoghurt in the protein good group and bread and pasta in the starchy food group. Under non-informative priors we would have somewhat weaker direct price intervention effects with only three food groups having oPE 95 per cent credibility interval estimates below –1. Only the vegetable and bread and pasta groups remain highly elastic, and fruits are becoming highly elastic.

With regard to impacts on other food groups through either substitution or complementary effects for foods within the same final food systems, the emerging picture is less clear. In Figure 3 we observe complementary effects in nine (10) out of the 28 cases with both a negative cPE estimate and the 95 per cent credibility interval containing only negative values under the expert (non-informative) prior. We only observe four (two) strong cases of substitutes with both positive coefficient estimates and interval values

FIGURE 3
Posterior Means and 95 per cent Credibility Intervals for Cross Price Elasticities (cPEs) under Expert Priors and Uninformative Priors. [Colour figure can be viewed at wileyonlinelibrary.com]



Note: Results are reported for the final stage systems; see Tables 5–7 for food group codings. 'G#' indicates the groups; and 'p#p#' indicates the number of the goods for the first and second items, respectively (see Fig. 1). This graph is for cPEs of goods inside the same final group, but 'G#' labels correspond to the second stage group.

under the expert (non-informative) prior. For example, we find that other non-alcoholic drinks are a complement to fruit drinks under the EP (G5p04p03 in Figure 3), while fruit drinks are found to be a substitute to other non-alcoholic drinks under both priors (G5p03p04 in Figure 3).

Focusing on the cPE point estimates in the final systems, we have a total of 16 (20) complementary relationships compared with 12 (5) substitutionary relationships within the final systems under expert (non-informative) priors. Depending on the nutritional value of these foods, it may support or lessen the impact of price-based policy interventions by pushing consumers into buying healthier products. In the context of soft drinks, between soft drinks and diet drinks the cPE point estimate and most of the support of the tighter posterior credibility interval under the EP suggest a complementary relationship with an increase in the soft drink price yielding consumers to consume more diet drinks that are lower in sugar. We can also look at the example of processed meat, a food group that is high in unhealthy SAFAs. If the government were to increase prices for this group of meat (such as a SAFA tax considered below), we would expect a statistically significant decrease in processed meat consumption. If prices of healthier meat options beef, pork and poultry were to increase, we would see a marginal statistically significant substitution into processed meat accompanied by a reduction in healthier meat consumption (see the results in Table 7). Note that processed and healthy meat groups are not in the same final system (not shown in Fig. 3).

In the remainder of the section, we illustrate the use of the PE estimates to assess the impact of three commonly considered policy scenarios: a tax on regular soft drinks, a subsidy of F&V and a tax on SAFA. In the first case, a main objective is the reduction of high sugar drink consumption and substitution with healthier options. In the second case, the aim is the increase in the consumption of both fruits and vegetables due to their beneficial nutritional content. In the third case the aim is the reduction in SAFA which is present in many different food groups. We

TABLE 8
Selected Own-Price Elasticity (oPE) Interval Estimates (Expert, Uninformative) and Prior

Type	Final Food Group (selected)	Expert		Uninformative		
		2.50%	97.50%	2.50%	97.50%	Prior (mean)
Other drinks	4. Other non-alcoholic	**−1.356**	**−1.176**	−1.158	−0.942	−0.99
Fruits and vegetables	5. Fruit	−0.988	−0.868	**−1.19**	**−1.046**	−0.58
	6. Vegetables	**−1.62**	**−1.464**	**−1.401**	**−1.241**	−0.88
High sugar	9. Ice cream	**−1.238**	**−1.03**	−0.636	−0.48	−1.74
	11. Chocolate confectionary	**−1.333**	**−1.165**	−0.958	−0.502	−1.27
	12. Pastry cook products	**−1.471**	**−1.295**	**−1.236**	**−0.976**	−1.52
Meat	17. Beef, lamb and hogget	−0.937	−0.757	−0.438	−0.234	−1.2
	18. Pork	**−1.133**	**−0.901**	−0.529	−0.293	−2.97
	19. Poultry	−0.775	−0.495	−0.457	−0.165	−1.51
Protein	20. Milk, yoghurt and eggs	**−1.55**	**−1.286**	−1.22	−0.968	−0.94
Starchy	23. Pasta and other cereal	**−1.408**	**−1.14**	−0.939	−0.715	−1.58

Note: Interval estimates and prior for oPEs of food groups with non-overlapping intervals under the different priors. Values shown in bold reflect the present elastic food groups.

investigate a 30 per cent SSB tax on soft drinks, 20 per cent subsidy on F&V and NZ$3 per 100 g tax on the SAFA content of a product. The magnitudes of these example policies were selected so that they are likely to have significant impact on food consumption, but also are realistic about a consumer's food budget.

In general, the expected change in demand can be predicted based on the Marshallian PEs and price variation from the policy change. However, an application of PEs in the usual manner (i.e., PE = % change in demand/% change in price) may break down as in particular the SAFA tax policy (and to a lesser extent the F&V subsidy policy) changes the total price index substantially. For example, a large price increase (e.g., 160 per cent increase for butter for the SAFA tax) combined with a large negative oPE may result in impossible negative consumption. To address this issue, we use the following formula to predict demand changes from policy interventions:

$$\%\Delta q \sim 100\% \times \left[e^{\ln\left(1+\frac{\varepsilon}{100}\right)\times\%\Delta p\times 100} - 1\right]. \tag{11}$$

Another advantage for policymakers is that the application of this formula does not require knowledge of demand shares equations (demand parameter estimates) which are not normally published in the literature. It should also be noted that in particular in demand systems such as the one considered here, the direct use of the demand share equations for predictions, as for example under the standard Bayesian predictive approach, is not straight forward because we predict budget shares rather than demands (quantities), and by construction, changes in budget shares should compensate each other (adding up constraint). It is not possible to recover quantities with the information at hand due to the use of price indices to allow for the aggregation of different physical demand units.

One advantage of the Bayesian approach is that predictions can be based on the full information from the posterior distribution of the elasticity parameters rather than only the point estimates. Thus, we can obtain both point estimates and intervals for the demand changes, which makes it a valuable tool to analyse impacts of possible policy scenarios (Bretteville-Jensen & Jacobi, 2011; Jacobi & Sovinsky, 2016). Here we use PE draws from the posterior distribution obtained from the estimation algorithm and under each compute demand changes based on formula (11). A, second advantage is that in addition to point estimates, interval estimates of predicted demand changes can be obtained directly without requiring additional mathematical or computational work.

Table 10 reports predicted demand changes under each of the three policy scenarios in terms of point predictions, and 95 per cent predictive intervals, for corresponding key targeted food groups. We first report (short-run) predicted

TABLE 9
Selected Cross-Price Elasticities (cPEs)

Type	Final food group (selected)		Expert 2.50%	Expert 97.50%	Uninformative 2.50%	Uninformative 97.50%	Prior (mean)
Fruit and vegetables	5. Fruit	6. Vegetables	−0.089	−0.001	−0.029	0.083	−0.25
	6. Vegetables	5. Fruit	**−0.062**	**−0.002**	**−0.176**	**−0.088**	−0.19
Dairy	8. Cheese cream	9. Ice cream	−0.023	0.141	**−0.314**	**−0.106**	0.44
High sugar	11. Chocolate confectionary	13. Sauces and condiments	−0.078	0.17	**−0.612**	**−0.108**	0.16
Meat	17. Beef and lamb	18. Pork	−0.028	0.096	**−0.217**	**−0.093**	0.65
	18. Pork	17. Beef and lamb	−0.019	0.201	**−0.381**	**−0.157**	0.65

Note: Interval estimates and prior for cPEs of food groups with non-overlapping intervals. Values shown in bold present a ‘significant’ complementary relationship.

demand changes based on the analysis of the VS data without including additional information, that is, under UIP, and then from the PE analysis under EP, centred at PEs elicited from two previous studies and weights of prior relative to data information (25 per cent, 50 per cent and 75 per cent) for each subsystem set by experts. Results under both priors agree in four out of the five (short-run) policy implications, although magnitudes and precision of estimates differ. First, regular soft drink consumption would reduce close to 20 per cent for a 30 per cent tax (18.7 per cent under UIP or 20.8 per cent under EP). In both cases it is not clear whether a sugar tax would increase demand for diet drinks. This clear reduction in soft drink demand but lack of robust conclusions on diet drink consumption (small positive effect) is consistent with the analysis of a recent soft drink tax in Catalonia (Puig-Codina *et al*., 2021). The regular soft drink demand changes are also consistent with the 15 per cent reduction in sugar sweetened drinks demand from a 20 per cent tax is predicted in Briggs *et al*. (2013) as well as with results reported in the survey by Thow *et al*. (2014) that include a reduction between 8 per cent and 22 per cent for a 20 per cent tax and 25 per cent reduction for the one study with a 30 per cent tax. We further find that under a 20 per cent subsidy for F&V demand would increase, with a larger change for fruits under UIP (27.9 per cent versus 21.1 per cent) and smaller change for vegetables under UIP (32.3 per cent versus 39.3 per cent), respectively. These predictions are within the range reported in Thow *et al*. (2014), who found demand increases for healthy foods, including for F&V, of at least half the magnitude of the subsidy. Finally, a tax on SAFA on NZ$3 per 100 g, with price implications ranging from a 13 per cent increase for pork, 50 per cent for margarine to 160 per cent for butter, would only reduce total food demand significantly under EP by 23.8 per cent for a NZ$3 per 100 g tax. Here total demand changes were reported in the Table 10 given the broader target of the tax which did entail a reduction in demand for butter and other high-fat product groups such as margarine and oil, pastry cook products, and cakes and biscuits. Overall, demand predictions under UIP exhibit a lower precision.

This first set of policy demand counterfactuals does not take into account possible changes in total expenditure on food (i.e., conditionality assumption). Especially in the longer run and given the size of the intervention and in some cases budget shares, one expects that if food prices increase substantially, then food expenditure will increase (at the expense of some other household expenditure beyond food). One way to adjust our short-run estimates based solely on PEs is using total food expenditure elasticities (TFE_e) (Blakely *et al*., 2020b). Two previous NZ studies gave TFE_e's of 0.83 and 0.68 (Michelini & Chatterjee, 1997; Michelini, 1999) and we accordingly used a TFE_e of 0.75. For example, if the pre-tax food expenditure were NZ\$150 for a family's weekly shop, and if the price index for food increases by 10 per cent following tax, then all purchasing will be scaled to achieve a total expenditure of NZ\$150 × (1 + 0.75 × 10%) = NZ\$161.25.

Scaling purchasing using the TFE_e (uniformly across all foods) implies that total expenditure on food increases by 8.3 per cent with the SAFA tax (8.3 per cent = the change in food price index of 11.0 per cent with SAFA tax multiplied by the TFE_e of 0.75). SSB tax results barely change with TFE_e adjustment (as the impact on total expenditure is minimal), but the F&V subsidy policy now shows a lesser increase in F&V purchasing (although still substantive at 14.3 per cent and 31.4 per cent) as consumers spend a bit less on total food expenditure, pocketing some of the subsidies rather than spending the same total. Likewise, for the SAFA policy with TFE_e adjustment, the demand reductions under SAFA are somewhat lower. Note that the results should be interpreted as responses of households who consume the food groups already. Since we do not explicitly model censoring, we may underestimate demand effects from households entering consumption of certain good groups after a policy effects change. As expected, demand changes (short and longer run) under the UIP, reported in the last two columns of Table 10 for comparison, overall show lower precision and some change in point predictions in terms of higher policy impacts on fruit consumption, lower impacts on vegetable consumption and less consumption reduction in SAFAs.

A full interpretation of the health impacts of food taxes and subsidies is beyond the scope of this paper. However, elsewhere we have used the Bayesian PEs estimated in this paper, and applied them to the total NZ population (and their dietary patterns) to estimate disease rate changes (e.g., cardiovascular disease, diabetes and various cancers) and changes in health-adjusted life-years for a range for food tax and subsidies (Blakely *et al*., 2020a).

IV Discussion

Policymakers need as accurate-as-possible estimations of the net impact of food taxes and subsidies. Natural experiments (with growing momentum from countries around the world introducing taxes and subsidies, including Mexico, Hungary, the UK and numerous others) (Backholer *et al*., 2017; Briggs *et al*., 2017; Colchero *et al*., 2017; Hagenaars *et al*., 2019) and randomised trials (Epstein *et al*., 2012; Niebylski *et al*., 2015; Afshin *et al*., 2017) can provide important evidence for policy. However, when policies are being newly considered – or applied in new contexts and ways – estimated PEs provide a vital tool for policy analysis. Improving PE estimation, in particular Marshallian PEs measuring the overall change in demand taking into account both the substitution effect and income effect, is essential to model the net impacts of food tax and subsidy policies onto nutritional outcomes (e.g., changes in SAFA or salt intake), then biological risk factors (e.g., blood pressure and body weight), and finally to health gains (e.g., quality-adjusted life-years) and costs (e.g., health system expenditure and productivity costs) (Ni Mhurchu *et al*., 2015; Cobiac *et al*., 2017; Cleghorn *et al*., 2019; Blakely *et al*., 2020a, 2020b).

This paper aims to add to the literature by introducing an approach to PE estimation for a large set of food groups that innovates: (i) the use of experimental data through 'virtual shopping' for a wide range of foods with exogenous price variation along dimensions of potential public health interventions and policy relevant food groupings; and (ii) the inclusion of published food PEs from previous observational studies within the analysis of multistage LAIDS via prior assumptions in a Bayesian estimation framework that are elicited within a optimisation-based approach that ensures key micro-economic assumptions and takes into account expert knowledge.

These innovations address several key challenges in existing approaches based on observational data, such as endogenous and insufficient price variations and unsuitable food groupings, limiting the validity and precision of currently available PE results and their use for reliable policy analysis. The paper exploits the computational strength of Bayesian methods and advances existing studies of demand (Tiffin & Arnoult,

Table 10
Estimated Percentage Changes from Policy Scenarios in Selected Food Groups

	Demand change predictions with posterior price elasticities distributions (%)			
	Short-run		Longer run (adjusted total food expenditure elasticities—TFE_e)	
Relevant key food groups	Uninformative prior	Expert prior	Uninformative prior	Expert prior
Regular soft drink	**−18.7** (−23.0, −14.1)	**−20.8** (−23.1, −18.3)	**−18.5** (−22.9, −14.0)	**−20.6** (−23.0, −18.1)
Diet soft drink	−1.64 (−7.29, 4.24)	1.91 (−1.32, 5.02)	−1.45 (−7.11, 4.43)	2.12 (−1.11, 5.23)
Fruit	**27.9** (26.1, 29.8)	**21.1** (19.9, 22.4)	**21.3** (19. 9, 22.8)	**14.3** (13.4, 15.2)
Vegetables	**32.3** (30.0, 34.5)	**39.3** (37.0, 41.6)	**25.4** (23.7, 27.2)	**31.4** (29.7, 33.2)
Saturated fat[a]	**−20.4** (−32.5, 4.9)	**−23.8** (−34.0, −3.1)	**−11.8** (−23.6, 10.9)	**−14.6** (−25.0, 4.6)

Note: Demand changes under three policy scenarios: a 30 per cent sugar-sweetened beverages (SSB) tax on soft drinks, a 20 per cent subsidy on fruits and vegetables, and NZ$3 per 100 g tax on saturated fat (SAFA) ([a]demand changes from SAFA are reported across all food groups as many food items contain SAFA). Estimates (expert and uninformative prior) shown in bold are for the foods targeted by the policy option. Credibility intervals of 95 per cent for demand changes are shown in parentheses under both prior scenarios and with and without adjustment for total food expenditure elasticity.

2008; Kasteridis *et al.*, 2011; Briggs *et al.*, 2013; Bilgic & Yen, 2014) to include food PEs from previous observational studies via prior assumptions in a Bayesian estimation framework with a focus on posterior PE estimates. To the best of our knowledge, the only attempt to use prior PEs in a Bayesian framework was a method paper by Dreze dated to the 1970s (Dreze, 1976). However, this study was done well before the Bayesian computational revolution in the early 1990s within a very simple demand framework. Our proposed prior elicitation approach ensures that prior PE information was incorporated in accordance with economic assumptions of the LAIDS model and the estimated multistage demand system.

Our paper also contributes to the small literature on estimating PEs from an experiment food demand setting (Ni Mhurchu *et al.*, 2009; Epstein *et al.*, 2012), providing the first Bayesian analysis in such a setting. In addition, this study contributes to the limited empirical evidence on PEs for foods that span all major food groups, including many foods relevant from a nutritional and health perspective. We show that incorporating suitable additional information and expert knowledge in the context of a multistage demand analysis of a moderate experimental sample can improve the precision of PE inference and counterfactual policy predictions, where the latter indicate beneficial nutritional outcomes from several pricing interventions (sugar tax, F&V subsidy, SAFA tax). This is partially a result of more pronounced price effects. Overall effects on precision and magnitudes using EP are stronger for cPEs than oPEs, which is consistent with the reported estimation and identification challenges for cPEs raised in the literature.

Supporting Information

Additional Supporting Information may be found in the online version of this article:

Table S1. Demand equations for drink groups (carbonated soft drinks & other non-alcoholic drinks).

Table S2. Demand equations for proteins groups (fish and seafood, meat, milk & eggs, processed meats).

Table S3. Demand equations for other food groups (butter, dairy, high sugar, margarine & oil, and other food groups).

Table S4. Marshallian cross- and oPEs matrix using a Bayesian LAIDS approach from the VS data in NZ.

Table S5. Marshallian SD for cross- and oPEs matrix using a Bayesian LAIDS approach from the VS data in NZ.

Table S6. Hicksian mean cross- and oPEs matrix using a Bayesian LAIDS approach from the VS data in NZ.

Table S7. Marshallian cross- and oPEs matrix using a Bayesian LAIDS approach from the VS data in NZ under uninformative prior (scale factor of 0.1).

Table S8. Marshallian SD cross- and oPEs matrix using a Bayesian LAIDS approach from the VS data in NZ under uninformative prior (scale factor of 0.1).

Table S9. Difference in PE Estimates for the Expert Prior and Uninformative Prior.

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Appendix A. Bayesian estimation framework of Multi-Stage LAIDS PE Estimation

A.1 Likelihood, Prior and Posterior

Let $\boldsymbol{w} = (\boldsymbol{w}_1,\ \boldsymbol{w}_2,\ \ldots,\ \boldsymbol{w}_H)$ denote the vector of budget shares for all shops in a demand system with $(n+1)$ food groups ($\boldsymbol{w}_h = (w_{1h},\ w_{2h},\ \ldots,\ w_{n+1h})$), and $\boldsymbol{\theta}$ being the vector of the group specific intercepts, price coefficients, and expenditure coefficients from Equation (1) ($\boldsymbol{\theta} = [\boldsymbol{\alpha}',\ \boldsymbol{\gamma}',\ \boldsymbol{\beta}']'$).

Arising from the microeconomic theory underlying the LAIDS model, Equation (1) is subject to the adding-up restrictions, $\sum_{i=1}^{n+1} \alpha_i = 1$, $\sum_{i=1}^{n+1} \gamma_{ij} = \sum_{i=1}^{n+1} \beta_i = 0$, homogeneity, $\sum_{j=1}^{n+1} \gamma_{ij} = 0$, and symmetry restrictions $\gamma_{ij} = \gamma_{ji}$. Due to the adding up conditions, one share equation must be dropped during estimation of the demand equations to avoid perfect multicollinearity (we recover the parameters for the last group using the adding-up restrictions). Here we drop the last share equation for food $(n+1)$ and assume that the first n elements in the error vector are normally distributed with $n \times n$ covariance matrix $\boldsymbol{\Sigma}$, $\varepsilon_h \sim \mathrm{N}(0,\ \boldsymbol{\Sigma})$.

We rewrite the LAIDS model defined by Equations (1) and (2) taking into account microeconomic restrictions in more compact notation as

$$w_{ih} = \boldsymbol{e}^{i'}\boldsymbol{\alpha} + \boldsymbol{P}^{i'}\boldsymbol{\gamma} + \boldsymbol{z}^{i'}\boldsymbol{\beta} + \varepsilon_{ih}, \tag{A1}$$

where

$$\boldsymbol{\alpha} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \\ . \\ . \\ . \\ \alpha_n \end{pmatrix}_{n\times 1} \quad \boldsymbol{\gamma} = \begin{pmatrix} \gamma_{11} \\ \gamma_{12} \\ . \\ . \\ . \\ \gamma_{1n} \\ \gamma_{22} \\ . \\ . \\ . \\ \gamma_{2n} \\ . \\ . \\ . \\ \gamma_{nn} \end{pmatrix}_{\left[\frac{n(n+1)}{2}\right]\times 1}, \quad \boldsymbol{\beta} = \begin{pmatrix} \beta_1 \\ \beta_2 \\ . \\ . \\ . \\ \beta_n \end{pmatrix}_{n\times 1}, \quad \boldsymbol{e}^1 = \begin{pmatrix} 1 \\ 0 \\ . \\ . \\ . \\ 0 \end{pmatrix}_{n\times 1}, \ \cdots, \ \boldsymbol{e}^n = \begin{pmatrix} 0 \\ 0 \\ . \\ . \\ . \\ 1 \end{pmatrix}_{n\times 1},$$

$$\boldsymbol{P}^{i'}_{1\times\left[\frac{n(n+1)}{2}\right]} = \left\{ \begin{array}{c} \boldsymbol{P}^{1'} = (\ \ln P_1 \quad \ln P_2 \ldots \quad \ln P_n \quad 0 \quad 0 \ldots 0\ ) \\ \boldsymbol{P}^{2'} = (\ 0 \quad \ln P_1 \ldots \quad 0 \quad \ln P_2 \ldots \quad \ln P_n\, 0 \ldots) \\ \ldots \\ \boldsymbol{P}^{n'} = (\ 0 \quad 0 \ldots \quad \ln P_1 \quad 0 \ldots \quad \ln P_2 \ldots \quad \ln P_n\ ) \end{array} \right\}$$

and

$$\mathbf{z}^1 = \begin{pmatrix} \mathrm{X_h/P_h} \\ 0 \\ . \\ . \\ . \\ 0 \end{pmatrix}_{\mathrm{n}\times 1}, \ \ldots, \ \mathbf{z}^{\mathrm{n}} = \begin{pmatrix} 0 \\ 0 \\ . \\ . \\ . \\ \mathrm{X_h/P_h} \end{pmatrix}_{\mathrm{n}\times 1}.$$

We can rewrite Equation (A1) as $w_{ih} = \boldsymbol{x}_h^{i'}\boldsymbol{\theta} + \varepsilon_{ih}$, $\boldsymbol{x}_h^{i'} = \left(\boldsymbol{e}^{i'},\ \boldsymbol{P}^{i'},\ \boldsymbol{z}^{i'}\right)$. Combining information on the demand of a household for all n food groups: $\boldsymbol{w}_h = \boldsymbol{x}_h\boldsymbol{\theta} + \boldsymbol{\varepsilon}_h$.

We can now express the likelihood for the demand shares of all households as

$$\ell(\boldsymbol{w}|\boldsymbol{\theta},\ \boldsymbol{\Sigma}) = \prod_{h=1}^{H} \mathrm{N}(\boldsymbol{x}_h\boldsymbol{\theta},\ \boldsymbol{\Sigma}), \tag{A2}$$

which has a multivariate normal structure. Hence the standard choices for the prior distribution is a normal prior for the mean coefficient vector $\boldsymbol{\theta}$ and a Wishart for the inverse of the symmetric and positive definite matrices $\boldsymbol{\Sigma}$ of the errors (see for example Chib & Greenberg, 1995; Kasteridis *et al.*, 2011)).

$$\pi\left(\boldsymbol{\theta},\ \boldsymbol{\Sigma}^{-1}\right) = \mathrm{N}(\boldsymbol{\theta}|\boldsymbol{\mu}_0,\ \boldsymbol{V}_0)W\left(\boldsymbol{\Sigma}^{-1}|\vartheta_0,\ \boldsymbol{R}_0\right), \quad \text{where } \vartheta_0 \geq n. \tag{A3}$$

The posterior distribution of the model parameters is then given by[1]

$$\pi\left(\boldsymbol{\theta},\ \boldsymbol{\Sigma}^{-1}|\boldsymbol{w}\right) \propto \mathrm{N}(\boldsymbol{\theta}|\boldsymbol{\mu}_0,\ \boldsymbol{V}_0)W\left(\boldsymbol{\Sigma}^{-1}|\vartheta_0,\ \boldsymbol{R}_0\right)\ell(\boldsymbol{w}|\boldsymbol{\theta},\ \boldsymbol{\Sigma}). \tag{A4}$$

A.2 MCMC Methods

While the posterior distribution is not tractable, the choices of prior distributions lead to an efficient estimation of the posterior distribution via Markov chain Monte Carlo (MCMC) methods using a 2-step Gibbs algorithm with a Normal update of the location parameters and a Wishart updated for the inverse of the covariance matrix. Below we outline the key steps of the sampler that includes an additional third step to compute the set of relevant elasticities.

For $g = 1$ to $(B + G)$ iterations, where B is the number of iterations in the burn-in period.

Step 0: Initialisation Σ^0

Step 1: Draw $\boldsymbol{\theta}^{(g)}$ from

$$\pi\left(\boldsymbol{\theta}^g|\boldsymbol{w},\ \Sigma^{(g-1)}\right) = N\left(\mathbf{b}^{(g)},\ \mathrm{B}^{(g)}\right),$$

[1]Technically, the posterior distribution is conditional to all simple information: shares, prices and expenditure.

where

$$\mathrm{B}^{(g)} = \left[\left(\sum_{h=1}^{H} \boldsymbol{x}'_h \Sigma^{-1(g-1)} \boldsymbol{x}_h\right) + \boldsymbol{V}_0^{-1}\right]^{-1}, \quad \text{and}$$

$$\mathbf{b}^{(g)} = \mathrm{B}^{(g)}\left[\left(\sum_{h=1}^{H} \boldsymbol{x}'_h \Sigma^{-1(g-1)} \boldsymbol{w}_h\right) + \boldsymbol{V}_0^{-1}\boldsymbol{\mu}_0\right].$$

Step 2: Draw $\Sigma^{-1(g)}$ from

$$\pi\left(\Sigma^{-1(g)} | \boldsymbol{w},\ \boldsymbol{\theta}^{(g)}\right) = W\left(\vartheta^{(g)},\ \boldsymbol{R}^{(g)}\right),$$

W is the Wishart distribution with

$$\vartheta^{(g)} = \vartheta_0 + H, \quad \text{and } \mathbf{R}^{(g)} = \left[\boldsymbol{R}_0^{-1} + \sum_{h=1}^{H}\left(\boldsymbol{w}_h - \boldsymbol{x}_h \boldsymbol{\theta}^{(g)}\right)\left(\boldsymbol{w}_h - \boldsymbol{x}_h \boldsymbol{\theta}^{(g)}\right)'\right]^{-1}.$$

Step 3 (Stage 1 or 1 Stage system): If $g > B$, compute elasticities:

$$\varepsilon_{ij}^{(g)} = \frac{\gamma_{ij}^{(g)} - \beta_i^{(g)}\overline{w_j}}{\overline{w_i}} - \rho_{ij}, \qquad \rho_{ij} = \left\{\begin{matrix} 1, & i = j \\ 0, & i \neq j \end{matrix}\right\}, \qquad \eta_i = \frac{\beta_i}{\overline{w_i}} + 1, \qquad \text{and} \quad \tilde{\varepsilon}_{ij} = \varepsilon_{ij} + \overline{w_j}\eta_i.$$

ε_{ij}, $\tilde{\varepsilon}_{ij}$ and η_i are Marshallian and Hicksian price elasticities, and expenditure elasticities, respectively, $\overline{w_j}$ are average shares.

A.3 Stage 2 and 3 Elasticities

We have in our application 11 demand systems for three stages which should be integrated in order to obtain the effects of policy interventions associated with tax and subsidies. Therefore, we propose a multiple stage LAIDS system, which is based on the assumption that the allocation of expenditure takes place in multiple conditional independent steps. Then, we can use the Edgerton approach in sequential stages to compute the price and expenditure elasticities. We use the first food group elasticities (fruit and vegetables, proteins, starchy grain foods, drinks and other food groups, see Fig. 2) to estimate the 2nd stage food groups elasticities (for instance, soft drinks and other non-alcoholic). Then, we use these elasticities in a further step to estimate the elasticities of the 3rd stage groups (for instance, regular and diet soft drinks). Therefore, we can estimate the total elasticities (Marshallian, Hicksian and expenditure) in the second stage as

$$\varepsilon_{ij} = \rho_{rs}\tilde{\varepsilon}_{(r)ij} + \eta_{(r)i}\overline{w}_{(s)j}\varepsilon_{(r)(s)}, \qquad \tilde{\varepsilon}_{ij} = \rho_{rs}\tilde{\varepsilon}_{(r)ij} + \eta_{(r)i}\overline{w}_{(s)j}\tilde{\varepsilon}_{(r)(s)}, \qquad \text{and} \quad \eta_i = \eta_{(r)i} \cdot \eta_{(r)},$$

where r and s refer to the first stage groups associated with 2nd stage goods i and j. $\rho_{rs} = 1$ if $s = r$ (zero if goods are in different first stage groups), $\overline{w}_{(s)j}$ is the average budget weight of good j in group s, $\tilde{\varepsilon}_{(r)ij}$ is the within group Hicksian PE of goods i and j in the second stage. $\eta_{(r)i}$ is the within group expenditure elasticity for i in the second stage, and $\varepsilon_{(r)(s)}$ the first stage Marshallian PEs for groups r and s. Hence Step 3 of the Gibbs sampler would now also involve the estimation of 2nd stage elasticities using relevant 1st stage elasticities.

We apply this approach to compute the total PEs for the 23 by 23 PE matrix, which is a combination of two and three stage systems. Posterior distributions of PEs, and their standard deviation (SD), can be calculated straightforwardly within the Bayesian framework using posterior parameter chains of each of the 11 demand systems, and previous equations.

Appendix B. Prior Demand Parameter Elicitation

B.1 Prior Means via Optimization Procedure

When solving optimization problem (10) to determine prior demand parameters based on the optimal elasticities, we define lower and upper bounds on elasticities to ensure that we can find an available set of parameters that satisfy simultaneously all restrictions. So, we set oPEs, $\varepsilon_{ii}^{Opt} \geq \varepsilon_{ii}^{G_l}/(1+b_i)$ and $\varepsilon_{ii}^{Opt} \leq \varepsilon_{ii}^{G_l}(1+b_i)$, b_i is such that ε_{ii}^{Opt} is between 97.56% and 102.5% from $\varepsilon_{ii}^{G_l}$. We also define bounds for the cross PEs, such that $\left|\varepsilon_{ij}^{Opt}\right| \leq 0.5\varepsilon_{ij}^{G_l}$, $i \neq j$, and $0 \leq \eta_i^{Opt} \leq 2$. Then, we impose symmetry constraints, $\gamma_{ij} = \gamma_{ji}$, so $\varepsilon_{ij}^{Opt} w_{i \in G_l}^{Prior} - \varepsilon_{ji}^{Opt} w_{j \in G_l}^{Prior} = \beta_j w_{i \in G_l}^{Prior} - \beta_i w_{j \in G_l}^{Prior}$, and adding-up constraints, summing all rows and columns for $\gamma = 0$, $\varepsilon_{n+1i}^{Opt} w_{j \in G_l}^{Prior} = \sum_{j=1}^{n+1} \beta_j w_{i \in G_l}^{Prior} - \rho_{ij} w_{j \in G_l}^{Prior}$ and $\varepsilon_{n+1i}^{Opt} w_{i \in G_l}^{Prior} = \sum_{j=1}^{n+1} \beta_i w_{j \in G_l}^{Prior} - \rho_{ij} w_{i \in G_l}^{Prior}$. We started the optimisation process for each food group with $b_i = 0$, and then increased it by a very small increment (i.e., 0.025) until the optimal solution for the elasticities was found. The lower/upper bounds for cPEs and expenditure elasticities were imposed based on our knowledge about elasticities in the literature. Recall that we are familiar with the elasticities in the literature, but not the hyperparameters in the demand equations since they are not normally published.

B.2 Scaling Factors for Expert Priors

To achieve relative weighting in the Bayesian analysis, scaling factors need specifying to weight the prior versus the data. Food system specific scaling factors were estimated as follows: First we set considered 19 possible scaling factors ranging from 0.00000001 to 100 (i.e. 0.00000001, 0.0000005, 0.0000001, …, 10, 50, 100) to reflect decreasing degrees of prior informativity. Second, we calculated oPEs for each demand system, using just sample information from the VS data, and the average elasticities using a Bayesian approach taking into account prior information at different scaling factors, solving our optimization program. In order to determine the scaling factor for the empirical analysis under expert priors we employed a group of four public health experts (In the original paper the experts were mentioned only in the acknowledgements): Prof Tony Blakely (School of Population Health, University of Melbourne), Dr Nhung Nghiem, Dr Cristina Cleghorn and Dr Anja Mizdrak (Department of Public Health, University of Otago). Professor Blakely and Drs Mizdrak, Nghiem and Cleghorn have an extensive and highly relevant expertise in food prices and diets, with over 30 research papers. For each demand system, we selected the scaling factor that achieved the expert's relative position: 25%, 50% or 75% of distance between the VS data and the prior. 50% means equal weighting between prior and data, and the ones in 25% percentile and 75% percentile for weighting towards priors or data, respectively.

Table B1

Scaling Factor for Each Demand System for Use in the Bayesian Model in Order to Combine the Information from Both Data and Priors

Stage	Demand system	Allocation of scale factor	Value of scaling factors	Notes
1	Food	Towards VS data	0.0001	
2	Drinks	Equal weight between VS data and priors	0.00025	
2	Fruit & Vegetables	Towards VS data	0.00025	
2	Other food category	Equal weight	0.005	Priors and data are all likely to be poor
2	Proteins	Towards VS data	0.001	
2	Bread & cereals	Towards VS data	0.00075	People likely to buy in supermarket
3	Soft drinks	Equal weight	0.00075	
3	Other non-alcoholic drinks	Equal weight	0.00075	
3	Dairy	Equal weight	0.001	Small number of observation 700/4500
3	High sugar food	Towards priors	0.0001	Vs less data, likely to be captured outside of supermarket data
3	Meat	Towards VS data	0.001	

Note: We thank Dr Cristina Cleghorn and Dr Anja Mizdrak for their help with identifying scaling factors for these demand systems.

TABLE B2
Prior PE Matrix that does not Satisfy the Microeconomic Restrictions

Food group	Drinks	Fruit and vegetables	Other food groups	Proteins	Starchy and Grain foods
Drinks	**−1.23**	−0.21	−0.08	0.51	−0.01
Fruit and vegetables	−0.09	**−0.72**	−0.24	−0.10	0.00
Other food groups	−0.15	−0.03	**−1.27**	0.13	−0.02
Proteins	0.16	−0.11	0.16	**−2.04**	0.01
Starchy and Grain foods	0.00	0.04	−0.03	0.16	**−1.09**

TABLE B3
Optimised Prior Marshallian PEs that Satisfy Demand Restrictions and be Included in the Model Results

Food group	Drinks	Fruit and vegetables	Other food groups	Proteins	Starchy and Grain foods
Drinks	**−1.23**	−0.48	0.36	0.50	−0.37
Fruit and vegetables	−0.14	**−0.72**	−0.49	0.50	−0.24
Other food groups	0.13	−0.41	**−1.27**	0.50	0.14
Proteins	0.14	0.39	0.38	**−2.03**	0.19
Starchy and Grain foods	−0.24	−0.49	0.27	0.50	**−1.09**