Thomas Bayes goes shopping: A virtual supermarket experiment and consumer response to price changes

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Outline

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Introduction

- Food price elasticities (PEs) are essential for evaluating impacts of food pricing interventions.
- Own-PEs measure the change in food demand in response to the change in its price.
  - For example, oPE beef = -0.7 → A 10% increase in the price of beef leads to a 7% decrease in beef purchase.

Introduction

- Cross-PEs measure the change in food demand in response to the change in the other food price.
  - A negative cPE indicates that two goods are complements.
  - A positive cPE indicates that two good are substitutes.
- For example, cPE beef and pork =0.05 suggests that a 10% increase in the price of pork leads to 0.5% increase in beef purchase.
- Cross-PEs can make a big impact on net health impacts, e.g. if increasing price of saturated fat 'just' shifts consumption to sugar

Introduction

- But food PEs are very difficult to estimate.
  - Firstly, existing econometric estimates of food PEs are often poor, being based on single observational data sets without much variation in prices.
  - Second, the food groupings are generally not defined in terms of relevant health outcomes (e.g., separating regular and diet soft drinks).
  - Finally, the econometric estimation of food demand systems typically relies on frequentist methods that fail to incorporate evidence from previous studies which could improve accuracy of PE estimates.

Two major innovations of this study

1. Uses a randomized experiment in a NZ Virtual Supermarket with price variations approximating those in proposed subsidy and tax policies.

Two major innovations of this study

2. Employs a Bayesian framework to incorporate prior PE estimates

- As no one dataset is perfect, and we do have prior information.
- To our knowledge, no one has done this before internationally.

Methods: An overview

1. Data: VS experiment

Data on purchases from 4258 supermarket trips from 1132 shoppers in a VS, with randomly selected price variations in foods

MODELLING

2. Multi-Stage Linear Almost Ideal Demand System (LAIDS)

3. PE priors

Published SPEND PE matrix for 24-by-24 food groups (Ni Mhurchu et al, 2015) and Sharma drinks PE matrix (Sharma et al, 2014)

→ Generate PE matrices for subsets of foods, using optimisation to satisfy econometric rules

4. Including Prior Information via Bayesian Analysis of LAIDS Model

Parametrize and specify for Bayesian functionality, especially accommodating priors on demand coefficients

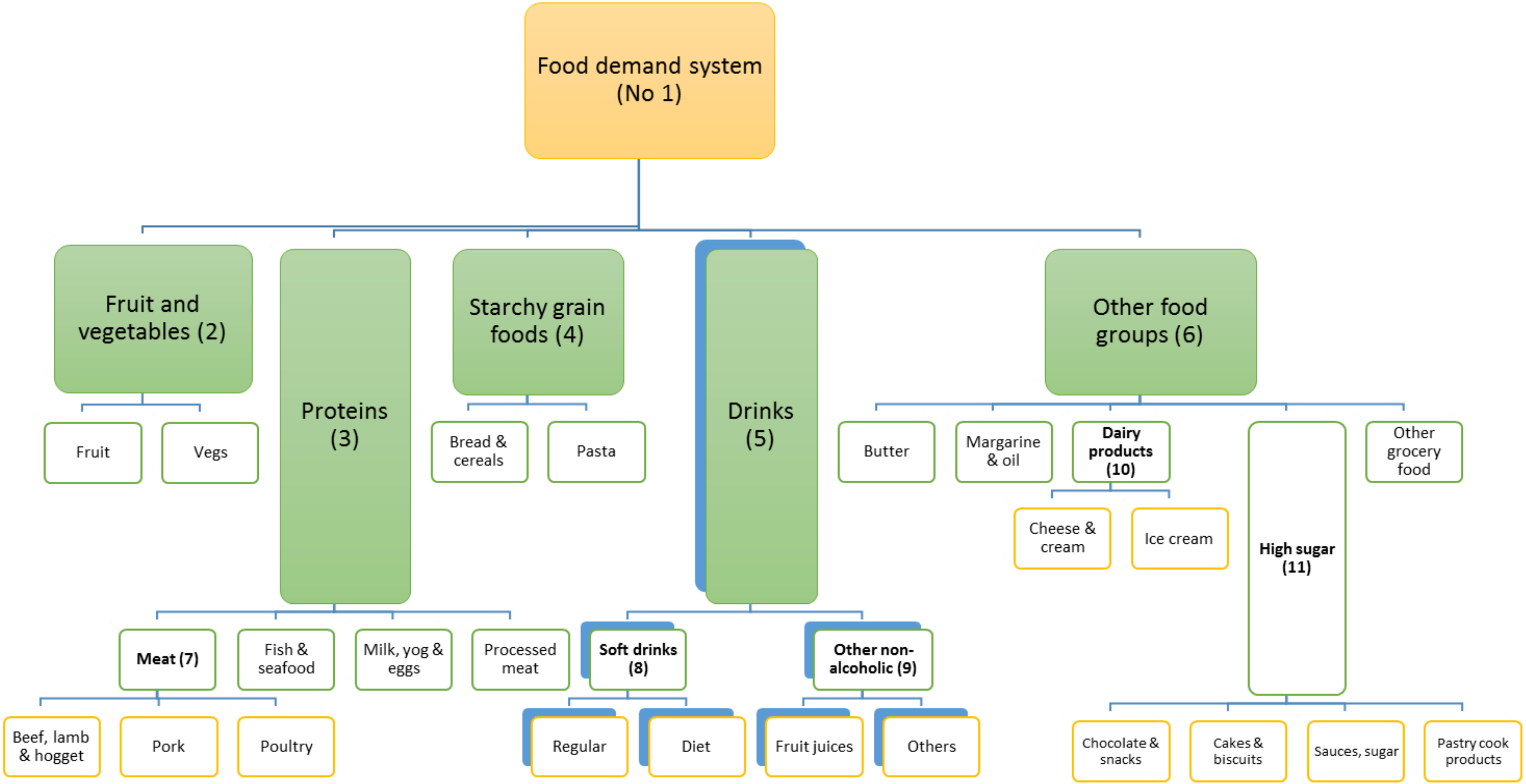
MCMC analyses using Gibbs sampler:

- 2000 burn in
- 5000 iterations generating coefficients for each of 11 food demand systems
- Within each iteration, use Edgerton aggregation formulas to generate one overall PE matrix for 23-by-23 food groups.

RESULTS

Overall PE matrix with central estimates and s.d. for each o- and c-PEs

Methods: Multi-stage approach food groupings



Empirical results: Marshallian PEs

Food	DSD	RSD	FJ	Other
Diet soft drinks (DSD)	**-0.627**	0.063	0.054	0.072
Regular soft drinks (RSD)	-0.082	**-0.774**	0.083	0.109
Fruit drinks & juices (FJ)	-0.056	-0.061	**-1.025**	0.240
Other non-alcoholic (Other)	-0.093	-0.102	-0.045	**-1.266**

A 10% increase in regular soft drinks price decreases its demand by 7.74%.

A 10% increase in regular soft drinks price leads to 0.63% increase in diet soft drinks purchase (cPE effect).

Preliminary results – not for citation without permission of Tony Blakely

Empirical results: Marshallian PEs (apparent complements shown in green)

Food	DSD	RSD	FJ	Other	FR	VEG
Diet soft drinks (DSD)	**-0.627**	0.063	0.054	0.072	0.005	0.010
Regular soft drinks (RSD)	-0.082	**-0.774**	0.083	0.109	0.007	0.016
Fruit drinks & juices (FJ)	-0.056	-0.061	**-1.025**	0.240	0.010	0.021
Other non-alcoholic (Other)	-0.093	-0.102	-0.045	**-1.266**	0.017	0.035
Fruit (FR)	0.000	0.000	0.000	0.001	**-0.928**	-0.032
Vegetables (VEG)	0.001	0.001	0.001	0.001	0.139	**-1.542**

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Empirical results: Marshallian PEs

Food	B	CC	IC	C&B	Choc	PCP	S&S	Marg
Butter (B)	**-0.306**	0.025	0.015	0.008	0.010	0.007	0.012	-0.104
Cheese cream (CC)	-0.021	**-1.077**	0.059	0.013	0.015	0.010	0.018	-0.071
Ice-cream (IC)	-0.022	0.067	**-1.134**	0.013	0.015	0.010	0.019	-0.075
Cakes & biscuits (C&B)	-0.034	0.009	0.005	**-1.007**	-0.073	0.039	-0.088	0.000
Chocolate confectionary (Choc)	-0.036	0.009	0.006	-0.080	**-1.249**	0.083	0.046	0.000
Pastry cook products (PCP)	-0.029	0.008	0.005	0.086	0.183	**-1.383**	0.144	0.000
Sauces & sugar condiments (S&S)	-0.048	0.012	0.007	-0.165	-0.063	-0.030	**-1.321**	0.000
Margarine (Marg)	-0.098	-0.025	-0.015	0.031	0.036	0.025	0.044	**-0.565**

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Discussion and conclusions

- The empirical analysis presents PE initial estimates for 23 food groups in NZ. Most of the oPEs were elastic, ranging from -0.3 to -2.6.
- There were strong substitute/complementary effects <u>within</u> food groups, however, the cross-PEs <u>between</u> food groups were small.
- Tony will talk to more substantive findings (eg, what does this PE matrix mean in terms of a F&V subsidy or a SSB tax)