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U.S. demand for organic and conventional vegetables: a Bayesian censored system approach

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Demand for organic and conventional vegetables is investigated using data from A.C. Nielsen's 2006 Homescan panel. We use a Bayesian Markov chain Monte Carlo technique, along with data augmentation, to estimate a large linear approximate Almost Ideal Demand System with censored dependent variables. Demands are price elastic, and expenditure elasticities are very high for organic vegetables, whilst demands for conventional vegetables are primarily inelastic. We find a mix of gross substitution and complementarity among the vegetable products, but net substitution is the dominant pattern. Socio-demographic characteristics also play important roles in demands. These findings can inform deliberations about marketing campaigns, nutrition education and policy interventions.

Key words: Bayesian MCMC, censored equation system, linear approximate Almost Ideal Demand System, national organic standard, Nielsen Homescan, organic vegetables.

1. Introduction

As global food demand continues to grow, new technologies have emerged as sustainable agricultural practices to meet food demand with environmental protection. Organic agriculture offers environmental benefits through management practices that enhance biodiversity and restore and maintain natural ecological harmony. Organic agriculture is developing rapidly worldwide. During 2007, 7.2 million hectares were operated by more than 180,000 organic farms in the European Union (EU) (22 per cent of world's total organic agricultural land), leading countries being Italy, Spain and Germany. During the same year, devoted to organic agricultural production were 6.4 million hectares in Latin American (led by Argentina, Brazil and Uruguay), 2.9 million hectares in Asia (led by China and India), 2.2 million hectares in North America (led by USA) and 900,000 hectares in Africa (Willer and Lukas 2010).

Globally, sales of organic food have increased by over five billion USD a year, reaching 46.1 billion in 2007 (Willer and Lukas 2010). In 2007, organic fruit and vegetables constitute the largest retail sales value ($6.9 billion) of all organic products in the USA, accounting for 37 per cent of the organic food

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sector (*Nutrition Business Journal* 2007). Elsewhere in the world, Germany sees the greatest demand for organic products in the EU, second only to the USA. Organic food sales increased from €1.48 billion in 1997 to €5.85 billion in 2008, accounting for 3.4 per cent of the food market (BMELV 2011).

Given the importance of organic food in today's agriculture, it is important to know the factors that determine its consumption. Studies have investigated consumer preferences towards organic food (e.g. Yiridoe *et al*. 2005). Most related to the current study is a demand system for organic and conventional frozen vegetables (Glaser and Thompson 1999), based on US monthly supermarket scanner data for 1990–1996. Two additional demand system studies investigate demand for organic and conventional beverage milk (Glaser and Thompson 2000), baby food (Thompson and Glaser 2001) and organic and conventional fresh fruits (Lin *et al*. 2009). Other studies focus on nonprice determinants of organic food demand. Thompson and Kidwell (1998) study consumer's choice of organic and conventional produce in Arizona, and Smith *et al*. (2009) investigate aggregate organic fruit and vegetable consumption using a US national sample, both focussing on binary-choice analysis.

Studies outside the USA investigate choice or purchase of organic produce in Norway (Torjusen *et al*. 2001), organic meat in the Nethelands (Verhoef 2005), organic food in Italy (Gracia and de Magistris 2008) and organic and integrated fruit and vegetables in Slovenia (Kuhar and Juvancic 2010), all with discrete-choice analysis. Wier *et al*. (2008) investigate demand in mature organic food markets in UK and Denmark, by estimating household organic budget share with OLS. Tsakiridou *et al*. (2006) analyse the influence of consumer characteristics and attitudes on the demand for organic olive oil in Greece, with a sample-selection model. Gracia and de Magistris (2008) review additional literature.

This study focusses on organic and conventional fresh vegetables. Unlike previous analyses with aggregate data in which household characteristics are compromised (Glaser and Thompson 1999, 2000; Thompson and Glaser 2001), we use micro-level data from A.C. Nielsen's Homescan panel. Our sample contains zero expenditures, notably in organic vegetables. With many zeros, conventional maximum-likelihood estimation is not feasible because of high-dimensional probability integrals in the likelihood function. We follow the Bayesian Markov chain Monte Carlo (MCMC) approach to censored equation systems – a viable alternative. An additional advantage of the procedure is various functions of the parameters such as demand elasticities can be characterised by draws from the posterior distributions, more easily than a classical approach.

2. The Nielsen Homescan panel

Data are drawn from Nielsen's Homescan panel, with a sample similar to that of the organic fruit studies in Lin *et al*. (2009). The panel consists of households that provide food-purchase data for at-home consumption and is repre-

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sentative of the US population. Nielsen provided a hand-held scanner to record grocery items purchased at retail outlets with the uniform product code (UPC). A subsample of households, called the 'Fresh Foods Panel', is supplied with a codebook that allows recording of non-UPC (random weight) items. This subsample is vital to the analysis of fresh vegetables. In 2006, the Fresh Foods Panel included 7534 households who reported purchases of food products with a UPC, such as packaged fresh vegetables, and as random weight at retail outlets. UPC-coded organic produce is identified by the presence of the USDA organic seal or organic claims created by Nielsen. For random-weight items, Nielsen uses a coding system that identifies organic produce. Socio-demographic information is also available. Note that data collection is subject to inadvertent recording and misestimated quantities, especially for random-weight items sold by count. Organic items are more likely to be sold in random-weight form than conventional items. Einav *et al.* (2008, p. 26) concluded that, although Homescan data contain recording errors, 'the overall accuracy of self-reported data by Homescan panelists seems to be in line with many other surveys of this type'.

Purchase records of fresh produce, reported weekly, are aggregated to the annual level. Despite such aggregation, the proportions of consuming households are very small for organic vegetables: potatoes (4.5 per cent), onions (6.1 per cent), tomatoes (13.2 per cent), carrots (19.6 per cent) and other vegetables (25.0 per cent) (Table 1). Organic peppers are consumed by only 3.27 per cent of the sample and are merged with other organic vegetables. Consuming proportions are higher for conventional vegetables, ranging from 64.2 per cent for peppers to 97.2 per cent for other vegetables. The large proportions of zero present formidable numerical difficulty in classical estimation, with 71.1 (11.33) per cent of the sample reporting five (seven) or more zeros. These high frequencies of zeros require evaluations of high-dimensional probability integrals in the likelihood function (Yen *et al.* 2003) and highlight the importance of the Bayesian approach.

For each product, the expenditure (\$/year) and quantity (lb./year) were recorded and price derived as the unit value. Prices for nonconsuming households are calculated with zero-order imputation, by replacing missing prices with the corresponding averages among consuming households in one of the 33 market areas where the household belongs. For organic onions, potatoes and tomatoes, which are heavily censored, price imputation is done with averages for four regions: East, Central, South and West. After deleting observations with missing information on important variables and observations with outliers in prices, the final sample contains 7120 households.

Mean expenditures on organic vegetables are small, ranging from \$3.42 per year on organic onions to \$11.40 on other organic vegetables among those consuming the respective commodities (Table 1). Mean expenditures on conventional vegetables are higher, ranging from \$9.15 on conventional peppers to \$55.68 on other conventional vegetables. Table 1 also presents sample statistics of quantities, prices and expenditure shares.

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Table 1 Sample statistics of expenditures, quantities, expenditure shares and prices

	Per cent	Expend. ($/year)		Quantity (lb./year)		Share		Price ($/lb.)	
Variable	Consuming	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Organic									
Carrots	19.62	1.04 (5.29)	4.17 (8.14)	0.93 (4.72)	4.43 (9.07)	0.009 (0.047)	0.038 (0.075)	1.37	0.30
Onions	6.11	0.21 (3.42)	1.44 (4.81)	0.21 (3.48)	1.36 (4.37)	0.002 (0.028)	0.010 (0.031)	1.05	0.23
Potatoes	4.49	0.27 (5.95)	2.11 (8.09)	0.33 (7.30)	2.61 (10.06)	0.002 (0.049)	0.018 (0.072)	1.03	0.22
Tomatoes	13.20	0.84 (6.37)	4.11 (9.63)	0.38 (2.88)	1.88 (4.43)	0.008 (0.057)	0.035 (0.079)	2.43	0.48
Other	24.99	2.42 (11.40)	11.40 (20.37)	1.25 (4.86)	7.20 (13.40)	0.017 (0.069)	0.062 (0.108)	6.05	7.30
Conventional									
Carrots	80.21	7.57 (9.43)	11.69 (12.36)	7.54 (9.39)	12.99 (13.89)	0.078	0.111	1.14	0.47
Onions	85.55	8.80 (10.29)	10.80 (11.00)	11.97 (13.99)	14.71 (14.99)	0.083	0.088	0.82	0.47
Peppers	64.17	5.87 (9.15)	11.58 (13.38)	3.85 (5.99)	7.07 (8.07)	0.044	0.066	1.48	0.64
Potatoes	86.78	15.19 (17.51)	16.53 (16.57)	32.11 (37.00)	36.76 (37.10)	0.163	0.165	0.57	0.29
Tomatoes	84.02	18.72 (22.28)	27.09 (28.18)	9.72 (11.57)	14.10 (14.67)	0.155	0.153	1.89	0.71
Other	97.22	54.14 (55.68)	61.20 (61.37)	35.88 (36.90)	42.49 (42.65)	0.439	0.200	1.36	1.05

Note: Sample size = 7120. Sample statistics of consuming households in parentheses. Organic peppers are merged with other organic vegetables; see text.

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Other explanatory variables include household size, and dummy variables indicating the presence of children, race and ethnicity, age, education, marital status of household head, employment status of the female head, regions and urbanisation. Definitions and sample statistics are presented in Table 2.

3. Model specification and estimation procedure

There is a large menu of econometric procedures for censored demand systems. Wales and Woodland (1983) develop an estimator from the Kuhn–Tucker conditions for constrained utility maximisation. Lee and Pitt (1986) take the dual approach, utilising notional demands and virtual prices to determine the regime-switching conditions of censored outcomes. Studies have followed both the Kuhn–Tucker (von Haefen *et al*. 2004) and dual approaches (Millimet and Tchernis 2008; Phaneuf *et al*. 2009). Applications of these approaches have been slow because demand systems so derived can be incoherent, which render maximum-likelihood estimates inconsistent unless regularity conditions of the utility function hold (van Soest *et al*. 1993). We follow the Tobit system approach (Amemiya 1974) as used in Yen *et al*. (2003) which, whilst less structural than the Kuhn–Tucker and virtual-price alternatives, avoids the conditions for statistical coherency, which are difficult to impose for flexible functional forms (van Soest *et al*. 1993).[1] Unlike the maximum simulated likelihood estimation in Yen *et al*. (2003), we use a Bayesian procedure to overcome numerical complexity with the multiple probability integrals in the classical approach.

Consider latent shares of the linear approximate Almost Ideal Demand System (LAIDS) (Deaton and Muellbauer 1980) for household h

$$s_h^* = \alpha x_h + \gamma \log P_h + \beta \log(M_h/P_h^*) + \varepsilon_h \tag{1}$$

where $s_h^* = [s_{h1}^*, \ldots, s_{hL}^*]'$ is L-vector of latent expenditure shares, x_h is K-vector of demographic variables, $P_h = [p_{h1}, \ldots, p_{hL}]'$ is L-vector of prices, M_h is total vegetable expenditure and $\varepsilon_h = [\varepsilon_{h1}, \ldots, \varepsilon_{hL}]'$ is L-vector of error terms. The log-price index $\log P_h^* = \Sigma_{i=1}^{L} \bar{s}_i \log(p_{hi})$, a geometric mean of component prices weighted by sample means of observed expenditure shares $\bar{s}_i$, differs from the log-linear analogue of the Laspeyres price index by an additive constant, which is inconsequential in estimation. This index is invariant to the units of measurement in P_h and ensures good approximation of the nonlinear AIDS by LAIDS (Moschini 1995). The parameters α, γ and β are $L \times K$, $L \times L$ and $L \times 1$, respectively. Adding-up restriction is imposed by $\iota'\alpha = [1, 0, \ldots, 0]$, $\iota'\beta = 0$, $\iota'\gamma = [0, \ldots, 0]$ and $\iota'\varepsilon = 0$, where ι is an L-vector of ones, as is symmetry by $\gamma = \gamma'$. Homogeneity holds given adding-up and symmetry.

[1] Millimet and Tchernis (2008) implement Lee and Pitt's (1986) dual approach with a Bayesian MCMC procedure, imposing conditions needed for local coherency with rejection sampling.

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Table 2 Definitions and sample statistics of socio-demographic variables

Variable	Definition	Mean
Continuous variables		
Household size	Number of members in households	2.33 (1.28)
Binary variables		
Child	Presence of a child(ren) age < 6	0.22
White	Race is white	0.74
Black	Race is black (reference)	0.13
Other race	Race is Hispanic, Asian or other	0.13
Age ≤40	Oldest head age ≤40	0.10
Age 41–64	Oldest head age 41–64	0.62
Age ≥65	Oldest head age ≥65 (reference)	0.29
High school	Maximum education of head is high school or lower	0.18
Some college	Maximum education of head is some college (reference)	0.30
College	Maximum education of head is college or higher	0.52
Married	Husband-wife household	0.59
Unemployed	Female head is unemployed	0.38
East	Resides in East region (of country)	0.22
Central	Resides in Central region	0.17
South	Resides in West region	0.38
West	Resides in West region (reference)	0.23
Urban	Resides in urban area	0.87

Note: Sample size = 7120. Standard deviations in parentheses.

We consider a Tobit system in which observed expenditure shares $s_h = [s_{h1}, \ldots, s_{hL}]'$ relate to latent shares s_h^* such that (Amemiya 1974)

$$\begin{aligned} s_{hi} &= s_{hi}^* \text{ if } s_{hi}^* > 0 \\ &= 0 \quad \text{if } s_{hi}^* \leq 0,\, h = 1, \ldots, N,\, i = 1, \ldots, L. \end{aligned} \tag{2}$$

Because the vector ε_h sums to zero, the error covariance matrix is singular and for estimation we exclude the last good, the elasticities of which are calculated with the adding-up restriction (Pudney 1989, p. 155; Yen *et al.* 2003). Assume error vector $\tilde{\varepsilon}_h = [\varepsilon_{h1}, \ldots, \varepsilon_{h,L-1}]'$ is $(L-1)$-dimensional independent and identically distributed normal with zero means and finite covariance matrix Σ with standard deviations σ_i and correlations ρ_{ij}:

$$\tilde{\varepsilon}_h \sim N_{L-1}(0, \Sigma) \tag{3}$$

where

$$\Sigma = \begin{bmatrix} \sigma_1^2 & \cdots & \sigma_1\sigma_{L-1}\rho_{1,L-1} \\ \vdots & \ddots & \vdots \\ \sigma_{L-1}\sigma_1\rho_{L-1,1} & \cdots & \sigma_{L-1}^2 \end{bmatrix}. \tag{4}$$

Using homogeneity, the $(L-1)$-element latent-share vector can be expressed as

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$$\tilde{s}_h^* = \tilde{\alpha} x_h + \tilde{\gamma} \log \tilde{P}_h + \tilde{\beta} \log(M_h / P_h^*) + \tilde{\varepsilon}_h \tag{5}$$

where $\tilde{P}_h = [p_{h1}/p_{hL}, \ldots, p_{h,L-1}/p_L]'$, $\tilde{\gamma}$ is a submatrix of γ with the Lth column and row removed, and $\tilde{\alpha}$ and $\tilde{\beta}$ are submatrix and subvector of α and β with the Lth row removed. Denote m-vector $\theta = [A, \Gamma, \tilde{\beta}']'$ such that $A = [\alpha_{11}, \ldots, \alpha_{1k}, \alpha_{21}, \ldots, \alpha_{2k}, \ldots, \alpha_{L-1,1}, \ldots, \alpha_{L-1,K}]$ comes from horizontal concatenation of the rows of $\tilde{\alpha}$ and $\Gamma = [\gamma_{11}, \ldots, \gamma_{1,L-1}, \gamma_{22}, \ldots, \gamma_{2,L-1}, \ldots, \gamma_{L-1,L-1}]$ contains upper-triangular elements of $\tilde{\gamma}$. Then, the latent-share vector (Eqn 5) can be expressed as

$$\tilde{s}_h^* = C_h \theta + \tilde{\varepsilon}_h \tag{6}$$

where C_h is an $(L-1) \times m$ matrix containing all explanatory variables from (Eqn 1). Construction of the data matrix C_h is demonstrated online (Data S1). Finally, define $[N(L-1)]$-vectors $\tilde{s}^* = [\tilde{s}_1^{*\prime}, \ldots, \tilde{s}_N^{*\prime}]'$ and $\tilde{s} = [\tilde{s}_1', \ldots, \tilde{s}_N']'$. Then, the augmented posterior distribution is

$$\begin{aligned} &p(\theta, \Sigma, \tilde{s}^* | \tilde{s}) \propto p(\tilde{s} | \tilde{s}^*, \theta, \Sigma) p(\tilde{s}^* | \theta, \Sigma) p(\theta) p(\Sigma) \\ &= \prod_{h=1}^{N} \left\{ \left[\prod_{i=1}^{L-1} \big(I(s_{hi} = 0) I(s_{hi}^* \le 0) + I(s_{hi}^* > 0) I(s_{hi} = s_{hi}^*) \big) \right] p(\tilde{s}_h^* | \theta, \Sigma) \right\} p(\theta) p(\Sigma) \end{aligned} \tag{7}$$

where $I(\cdot)$ is a binary indicator function and $p(\theta)$ and $p(\Sigma)$ are priors. The posterior simulator is implemented by sequentially drawing the conditional posteriors $p(\tilde{s}^* | \tilde{s}, \theta, \Sigma)$, $p(\theta | \tilde{s}^*, \Sigma)$ and $p(\Sigma | \tilde{s}^*, \theta)$. The procedure described here extends the Bayesian MCMC procedure for seemingly unrelated regression (SUR) (Geweke 2005, pp. 162–169) by one additional step – data augmentation by drawing the conditional posterior $p(\tilde{s}^* | \tilde{s}, \theta, \Sigma)$ and including drawn latent data along with the observed data in the posterior distribution (Tanner and Wong 1987; Albert and Chib 1993). This procedure extends the single equation Tobit estimation procedure of Chib (1992). Huang (2001) applies the procedure to a bivariate-censored SUR without cross-equation restrictions, Tiffin and Arnoult (2010) extend the procedure to an infrequency-of-purchase system and Kasteridis *et al.* (2011) to a censored LAIDS. Details of the MCMC algorithm are available online (Data S1).

Note that the assumption of joint normal distribution for the error vector ε_h in (Eqn 1) is strictly inconsistent with the share system specification, as it ignores the requirement that shares be within the unit simplex by giving positive probability to shares outside the simplex (Woodland 1979). This normality assumption can be problematic for shares close to one. Remedial options include the use of other error distributions such as the Dirichlet distribution (Woodland 1979), and a mapping mechanism suggested by Wales and Woodland (1983, p. 270) and used in Kasteridis *et al.* (2011). However, the

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mapping approach requires at least one good that is always consumed, which we do not have in the current application. As a practical matter, however, our observed shares are much less than one relative to the estimated error standard deviations, with sample means under 0.08 for all organic vegetables and with the largest mean in other conventional vegetables (0.44).

4. Estimation results and diagnostics

We estimate the system with other conventional vegetables excluded. We run our MCMC algorithm for 30,000 replications. Burn-ins and skips are determined by a series of diagnostics. First, collecting every replication after 3000 replications for the burn-in phase gives autocorrelation functions that die off after <10 lags for most of the parameters except the error standard deviations (σ_i) and expenditure coefficients (β_i) of all (five) organic vegetables. Even after skipping 10 replications, autocorrelations for organic onions and organic potatoes are present up to the fifth lag, possibly due to severe censoring in these two goods. Thus, to ensure that our MCMC draws are independent, we run the algorithm for 30,000 replications and collect every 30th replication after discarding the first 3000 of the burn-in phase. The remaining 900 draws are used to obtain means and standard deviations of the posterior densities and elasticities, and their 95 per cent highest posterior density (HPD) intervals (Chen *et al*. 2000, p. 219).

To assess the performance of the MCMC algorithm, we use trace plots and cumulative average plots, autocorrelation functions and Geweke's (1992) Chi-squared test on the means of the first 20 per cent versus last 50 per cent of the draws. Geweke's Chi-square test suggests the sample of draws attained an equilibrium state for 257 of 270 coefficients. Trace plots for the 13 coefficients failing the test nevertheless indicate convergence and good mixing behaviour of the chains; two sets of the plots are available online Data S1.

Space limitation prohibits presentation of parameter estimates (Data S1), which we summarise. At a high (95 per cent) posterior probability (of being nonzero), all demographic variables are 'significant' (in the classical sense) in at least two equations. College and Central are significant in seven equations. Nearly 60 per cent (or 32) of the 55 price coefficients are significant, as are all but one expenditure coefficients, all error standard deviations, and 80 per cent (36) of the 45 error correlation coefficients.

5. Elasticities

Denote the deterministic shares of LAIDS in (Eqn 1) as $h_{hi}(\theta)$, univariate standard normal cumulative distribution function as $\Phi(\cdot)$ and probability density function as $\varphi(\cdot)$. Then, the unconditional means of expenditure shares are

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$$E(s_{hi}) = \Phi[h_{hi}(\theta)/\sigma_i]\, h_{hi}(\theta) + \sigma_i \varphi[h_{hi}(\theta)/\sigma_i]. \quad (8)$$

Marshallian own-price and expenditure elasticities for the first $L - 1$ goods are obtained by differentiating (Eqn 8):

$$e_{ij}^h = -\delta_{ij} + \frac{\partial E(s_{hi})}{\partial p_{hj}} \frac{p_{hj}}{\partial E(s_{hi})} \quad (9)$$

$$\eta_i^h = -1 + \frac{\partial E(s_{hi})}{\partial M_h} \frac{M_h}{\partial E(s_{hi})} \quad (10)$$

for all $i = 1,\ldots,L - 1$, $j = 1,\ldots,L$, $h = 1,\ldots,N$, where δ_{ij} is the *Kronecker delta*. Elasticities with respect to demographic variables are derived in like manner. Then, elasticities for the Lth good are derived using adding-up and compensated elasticities by the Slutsky equation (Yen *et al*. 2003). Elasticities are evaluated for all observations and averaged over the sample ($h = 1, \ldots, N$). These calculations are repeated for all retained MCMC draws, and the resulting elasticities used to obtain means, standard deviations and HPD intervals.

5.1. Price and expenditure elasticities

Table 3 presents uncompensated price and expenditure elasticities.[2] All own-price elasticities are negative with a high (95 per cent) posterior probability. Demand for all organic vegetables are elastic, with own-price elasticities ranging from −1.81 for other organic vegetables to −2.77 for organic potatoes. These elasticities are comparable with those reported for organic frozen vegetables by Glaser and Thompson (1999), which range between −1.34 and −2.26; they also differ notably from the own-price elasticities for organic fruits reported by Lin *et al*. (2009) based on the same data source as the current study, which range from −0.01 to −3.54. Demand for conventional vegetables is much smaller – inelastic except potatoes, which has an own-price elasticity of −1.20. These own-price elasticities are much greater than the estimates for conventional fruits reported by Lin *et al*. (2009). All expenditure elasticities for organic vegetables exceed unity, ranging from 1.30 for organic carrots to 1.84 for organic potatoes. Expenditure elasticities for conventional vegetables are considerably smaller except conventional peppers (1.29), ringing around unity for conventional carrots (with a 95 per cent HPD interval including 1), onions and potatoes and well below unity

[2] Estimation by excluding conventional potatoes and conventional tomatoes, respectively, produced fairly similar uncompensated and compensated elasticities, in reference to their standard errors, for most goods, except those for the omitted equation. These additional elasticity estimates are available online (Data S1).

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Table 3 Uncompensated price and expenditure elasticities

	Organic vegetables					Conventional vegetables						
	Carrots	Onions	Potatoes	Tomatoes	Other	Carrots	Onions	Peppers	Potatoes	Tomatoes	Other	Expenditure
Organic vegetables												
Carrots	−1.854*	−0.126	0.095	0.242*	−0.080*	0.117	0.086	0.073	0.040	−0.079	0.197*	1.289*
	(−2.058)	(−0.295)	(−0.105)	(0.066)	(−0.166)	(−0.004)	(−0.036)	(−0.033)	(−0.097)	(−0.211)	(0.074)	(1.224)
	[−1.652]	[0.061]	[0.287]	[0.423]	[−0.010]	[0.256]	[0.196]	[0.172]	[0.180]	[0.055]	[0.304]	[1.359]
Onions	−0.218	−1.903*	0.743*	0.013	−0.476*	−0.131	0.083	0.218*	−0.116	−0.396*	0.471*	1.712*
	(−0.530)	(−2.251)	(0.437)	(−0.282)	(−0.609)	(−0.389)	(−0.148)	(0.024)	(−0.383)	(−0.610)	(0.261)	(1.573)
	[0.078]	[−1.524]	[1.122]	[0.327]	[−0.344]	[0.099]	[0.320]	[0.416]	[0.122]	[−0.138]	[0.692]	[1.862]
Potatoes	0.096	0.478*	−2.767*	0.392*	−0.199*	−0.354*	−0.252*	0.036	0.145	−0.228*	0.815*	1.838*
	(−0.108)	(0.255)	(−3.131)	(0.141)	(−0.325)	(−0.536)	(−0.415)	(−0.128)	(−0.067)	(−0.447)	(0.576)	(1.673)
	[0.316]	[0.711]	[−2.430]	[0.643]	[−0.069]	[−0.159]	[−0.087]	[0.178]	[0.378]	[−0.030]	[1.079]	[2.019]
Tomatoes	0.221*	0.010	0.337*	−1.858*	−0.273*	−0.097	0.145*	−0.042	0.036	−0.205*	0.424*	1.303*
	(0.059)	(−0.163)	(0.119)	(−2.077)	(−0.356)	(−0.233)	(0.015)	(−0.150)	(−0.099)	(−0.354)	(0.289)	(1.224)
	[0.386]	[0.167]	[0.532]	[−1.637]	[−0.201]	[0.038]	[0.264]	[0.072]	[0.195]	[−0.063]	[0.563]	[1.391]
Other	−0.064*	−0.221*	−0.137*	−0.237*	−1.812*	0.028	0.044*	0.008	0.196*	0.019	0.699*	1.478*
	(−0.130)	(−0.279)	(−0.229)	(−0.305)	(−1.875)	(−0.023)	(0.006)	(−0.035)	(0.132)	(−0.047)	(0.604)	(1.412)
	[−0.006]	[−0.162]	[−0.047]	[−0.173]	[−1.747]	[0.084]	[0.088]	[0.048]	[0.259]	[0.085]	[0.794]	[1.549]
Conventional vegetables												
Carrots	0.068*	−0.022	−0.129*	−0.039	0.040*	−0.767*	−0.068*	−0.050*	−0.041	0.016	−0.025	1.015*
	(0.009)	(−0.096)	(−0.213)	(−0.110)	(0.010)	(−0.824)	(−0.114)	(−0.086)	(−0.092)	(−0.033)	(−0.067)	(0.989)
	[0.136]	[0.043]	[−0.048]	[0.035]	[0.076]	[−0.704]	[−0.031]	[−0.010]	[0.007]	[0.064]	[0.019]	[1.040]
Onions	0.060	0.046	−0.092*	0.101*	0.057*	−0.082*	−0.887*	−0.079*	−0.049	−0.045	−0.103*	1.074*
	(−0.004)	(−0.031)	(−0.185)	(0.030)	(0.028)	(−0.132)	(−0.941)	(−0.114)	(−0.097)	(−0.091)	(−0.143)	(1.052)
	[0.122]	[0.120]	[−0.019]	[0.177]	[0.084]	[−0.039]	[−0.826]	[−0.038]	[0.002]	[0.001]	[−0.061]	[1.094]
Peppers	0.063	0.113*	0.051	−0.027	0.023	−0.100*	−0.130*	−0.961*	−0.005	−0.103*	−0.212*	1.289*
	(−0.017)	(0.024)	(−0.049)	(−0.114)	(−0.017)	(−0.161)	(−0.178)	(−1.030)	(−0.069)	(−0.170)	(−0.270)	(1.257)
	[0.138]	[0.204]	[0.170]	[0.074]	[0.062]	[−0.040]	[−0.074]	[−0.895]	[0.056]	[−0.040]	[−0.156]	[1.324]
Potatoes	0.025	0.000	0.077*	0.027	0.101*	−0.030*	−0.028*	0.012	−1.201*	0.032	−0.104*	1.088*
	(−0.016)	(−0.047)	(0.020)	(−0.014)	(0.080)	(−0.061)	(−0.055)	(−0.011)	(−1.247)	(−0.007)	(−0.144)	(1.069)
	[0.065]	[0.041]	[0.139]	[0.080]	[0.127]	[−0.003]	[−0.003]	[0.037]	[−1.154]	[0.068]	[−0.071]	[1.111]

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Table 3 (*Continued*)

	Organic vegetables					Conventional vegetables						
	Carrots	Onions	Potatoes	Tomatoes	Other	Carrots	Onions	Peppers	Potatoes	Tomatoes	Other	Expenditure
Tomatoes	−0.011	−0.052*	−0.028	−0.053*	0.035*	0.010	−0.021	−0.024	0.042	−0.814*	−0.113*	1.028*
	(−0.051)	(−0.091)	(−0.087)	(−0.103)	(0.010)	(−0.021)	(−0.045)	(−0.050)	(−0.001)	(−0.863)	(−0.154)	(1.007)
	[0.031]	[−0.005]	[0.027]	[−0.006]	[0.060]	[0.040]	[0.006]	[0.001]	[0.076]	[−0.768]	[−0.076]	[1.049]
Other	−0.019	0.017	0.025	0.019	−0.034*	−0.013	0.020*	0.026*	0.080*	−0.063*	−0.908*	0.849*
	(−0.040)	(−0.005)	(−0.005)	(−0.007)	(−0.047)	(−0.028)	(0.006)	(0.013)	(0.061)	(−0.081)	(−0.926)	(0.836)
	[0.003]	[0.040]	[0.054]	[0.043]	[−0.023]	[0.002]	[0.035]	[0.039]	[0.098]	[−0.046]	[−0.887]	[0.860]

Note: 95% lower highest posterior density (HPD) interval in parentheses, 95% higher HPD interval in brackets. Asterisk indicates that the 95% interval does not include zero.

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for other conventional vegetables (0.85). Of the 110 cross-price elasticities, over half are significant, suggesting a mix of gross complements (32 elasticities) and substitutes (26 elasticities). The largest cross-price effects are seen in other conventional vegetables, which are gross substitute to all organic vegetables, with cross-price elasticities ranging from 0.20 (with organic carrots) to organic potatoes (0.82), and gross complement to all other conventional vegetables except carrots, which is insignificant. We find gross substitution between some of the conventional vegetables and their organic counterparts – specifically in carrots, potatoes and other vegetables. Glaser and Thompson (1999) also report gross substitution among organic and conventional frozen vegetables. All other uncompensated cross-price elasticities are much smaller (e.g. <0.2).

Compensated price elasticities are presented in Table 4. All compensated own-price elasticities have a high (>95 per cent) posterior probability of being negative and, as expected, smaller than their uncompensated counterparts because all expenditure elasticities are positive. In addition, all compensated own-price elasticities are above unity for all organic vegetables, and below unity for conventional vegetables expect potatoes (−1.02). Over half (or 67) of the cross-price elasticities have a high (>95 per cent) posterior probability of being nonzero. Whilst the uncompensated cross-price elasticities suggest a mix of gross substitutes and complements, the compensated elasticities suggest that net substitution (57 elasticities) is the more obvious pattern than net complementarity (10 elasticities). Net complementarity is found primarily in organic onions, potatoes and tomatoes, which all have net complementary relationship with other organic vegetables. For no obvious reason, net complementary relationship exists between conventional carrots and organic potatoes.

In sum, the significant effects of own- and cross-prices, compensated and uncompensated, and total expenditure are compelling and highlight the importance of modelling the demand in a utility-theoretic framework. Non-price effects reported in the previous studies are likely biased. An important marketing and policy implication of these price and expenditure elasticities is that prices and income do play important roles in the demand for organic and conventional vegetables.

5.2. Roles of demographic variables

Consumption of conventional potatoes increases with household size (elasticity = 0.17) but consumption of organic carrots (−0.20), potatoes (−0.56), other organic vegetables (−0.18) and other conventional vegetables (−0.05) decreases (Table 5). Household size increases organic olive oil consumption in Greece (Tsakiridou *et al.* 2006) but has an opposite impact on organic food consumption in the UK (Wier *et al.* 2008).

Presence of children increases consumption of organic and conventional carrots but has a negative effect on conventional tomatoes, all at small

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Table 4 Compensated price elasticities

	Organic vegetables					Conventional vegetables					
	Carrots	Onions	Potatoes	Tomatoes	Other	Carrots	Onions	Peppers	Potatoes	Tomatoes	Other
Organic vegetables											
Carrots	−1.839*	−0.123	0.099	0.253*	−0.053	0.231*	0.200*	0.134*	0.261*	0.128	0.711*
	(−2.043)	(−0.292)	(−0.102)	(0.077)	(−0.135)	(0.109)	(0.079)	(0.031)	(0.128)	(−0.007)	(0.586)
	[−1.638]	[0.063]	[0.291]	[0.434]	[0.020]	[0.371]	[0.311]	[0.233]	[0.400]	[0.259]	[0.824]
Onions	−0.198	−1.900*	0.747*	0.028	−0.442*	0.020	0.234	0.299*	0.178	−0.121	1.155*
	(−0.511)	(−2.247)	(0.441)	(−0.266)	(−0.575)	(−0.238)	(−0.015)	(0.110)	(−0.085)	(−0.337)	(0.932)
	[0.097]	[−1.521]	[1.126]	[0.341]	[−0.310]	[0.247]	[0.455]	[0.504]	[0.404]	[0.134]	[1.379]
Potatoes	0.117	0.482*	−2.762*	0.408*	−0.163*	−0.192	−0.090	0.123	0.460*	0.067	1.549*
	(−0.085)	(0.252)	(−3.126)	(0.159)	(−0.288)	(−0.372)	(−0.268)	(−0.009)	(0.233)	(−0.130)	(1.271)
	[0.338]	[0.709]	[−2.425]	[0.659]	[−0.033]	[0.010]	[0.056]	[0.297]	[0.678]	[0.275]	[1.799]
Tomatoes	0.236*	0.013	0.340*	−1.847*	−0.247*	0.018	0.260*	0.020	0.260*	0.004	0.943*
	(0.074)	(−0.160)	(0.122)	(−2.065)	(−0.327)	(−0.115)	(0.127)	(−0.089)	(0.130)	(−0.146)	(0.803)
	[0.401]	[0.170]	[0.536]	[−1.627]	[−0.172]	[0.161]	[0.377]	[0.135]	[0.421]	[0.142]	[1.085]
Other	−0.047	−0.218*	−0.133*	−0.224*	−1.784*	0.159*	0.175*	0.078*	0.451*	0.256*	1.288*
	(−0.113)	(−0.276)	(−0.226)	(−0.289)	(−1.848)	(0.109)	(0.132)	(0.036)	(0.382)	(0.186)	(1.187)
	[0.011]	[−0.159]	[−0.044]	[−0.157]	[−1.719]	[0.218]	[0.214]	[0.120]	[0.509]	[0.318]	[1.388]
Conventional vegetables											
Carrots	0.079*	−0.020	−0.126*	−0.030	0.061*	−0.677*	0.021	−0.001	0.133*	0.179*	0.380*
	(0.021)	(−0.094)	(−0.211)	(−0.101)	(0.029)	(−0.735)	(−0.024)	(−0.036)	(0.081)	(0.128)	(0.338)
	[0.147]	[0.045]	[−0.045]	[0.044]	[0.094]	[−0.614]	[0.057]	[0.040]	[0.179]	[0.225]	[0.429]
Onions	0.072*	0.049	−0.090*	0.111*	0.079*	0.013	−0.793*	−0.028	0.135*	0.127*	0.324*
	(0.008)	(−0.028)	(−0.183)	(0.033)	(0.052)	(−0.033)	(−0.846)	(−0.063)	(0.084)	(0.083)	(0.282)
	[0.135]	[0.122]	[−0.016]	[0.180]	[0.108]	[0.060]	[−0.731]	[0.012]	[0.182]	[0.175]	[0.366]
Peppers	0.078	0.116*	0.054	−0.015	0.049*	0.013	−0.017	−0.899*	0.215*	0.103*	0.303*
	(−0.002)	(0.027)	(−0.045)	(−0.102)	(0.008)	(−0.043)	(−0.066)	(−0.963)	(0.151)	(0.045)	(0.241)
	[0.153]	[0.207]	[0.173]	[0.085]	[0.089]	[0.077]	[0.039]	[−0.828]	[0.276]	[0.174]	[0.355]
Potatoes	0.038	0.002	0.080*	0.037	0.123*	0.066*	0.068*	0.064*	−1.015*	0.206*	0.330*
	(−0.003)	(−0.044)	(0.024)	(−0.008)	(0.100)	(0.035)	(0.042)	(0.040)	(−1.063)	(0.170)	(0.297)
	[0.077]	[0.044]	[0.143]	[0.086]	[0.147]	[0.095]	[0.094]	[0.089]	[−0.970]	[0.244]	[0.372]

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Table 4 (*Continued*)

	Organic vegetables					Conventional vegetables					
	Carrots	Onions	Potatoes	Tomatoes	Other	Carrots	Onions	Peppers	Potatoes	Tomatoes	Other
Tomatoes	0.001	−0.049*	−0.025	−0.044	0.056*	0.100*	0.069*	0.025*	0.218*	−0.649*	0.296*
	(−0.039)	(−0.089)	(−0.084)	(−0.094)	(0.029)	(0.068)	(0.045)	(0.001)	(0.179)	(−0.700)	(0.255)
	[0.043]	[−0.003]	[0.029]	[0.003]	[0.079]	[0.130]	[0.095]	[0.052]	[0.254]	[−0.604]	[0.336]
Other	−0.010	0.019	0.027	0.026	−0.017*	0.062*	0.094*	0.066*	0.225*	0.074*	−0.567*
	(−0.030)	(−0.003)	(−0.004)	(0.000)	(−0.029)	(0.047)	(0.080)	(0.052)	(0.206)	(0.056)	(−0.586)
	[0.014]	[0.042]	[0.056]	[0.050]	[−0.005]	[0.077]	[0.108]	[0.078]	[0.245]	[0.092]	[−0.545]

See footnote to Table 3.

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Table 5 Elasticities with respect to demographic variables

	Household size	Child	White	Other race	Age ≤40	Age 41–64	High school	College	Married	Unemployed	East	Central	South	Urban
Organic vegetables														
Carrots	−0.201*	0.064*	0.225*	0.013	0.037*	0.115*	−0.026	0.114*	0.145*	0.003	−0.053*	−0.080*	−0.088*	0.042
	(−0.410)	(0.018)	(0.076)	(−0.021)	(0.016)	(0.014)	(−0.067)	(0.047)	(0.043)	(−0.049)	(−0.096)	(−0.119)	(−0.153)	(−0.124)
	[−0.021]	[0.105]	[0.382]	[0.045]	[0.060]	[0.219]	[0.013]	[0.186]	[0.231]	[0.057]	[−0.012]	[−0.040]	[−0.016]	[0.225]
Onions	−0.106	−0.001	−0.302*	−0.023	0.052*	0.066	−0.011	0.060	−0.052	0.039	−0.039	−0.076*	−0.135*	−0.351*
	(−0.430)	(−0.089)	(−0.570)	(−0.083)	(0.012)	(−0.133)	(−0.076)	(−0.071)	(−0.230)	(−0.067)	(−0.123)	(−0.138)	(−0.259)	(−0.678)
	[0.261]	[0.094]	[−0.007]	[0.030]	[0.098]	[0.247]	[0.060]	[0.188]	[0.108]	[0.137]	[0.035]	[−0.004]	[−0.021]	[−0.025]
Potatoes	−0.591*	0.086	−0.343*	−0.063	−0.002	0.013	−0.016	0.199*	−0.059	0.107*	−0.085	−0.081	−0.108	0.506*
	(−1.064)	(−0.022)	(−0.682)	(−0.131)	(−0.057)	(−0.213)	(−0.098)	(0.044)	(−0.271)	(0.002)	(−0.187)	(−0.170)	(−0.233)	(0.130)
	[−0.150]	[0.207]	[−0.023]	[0.018]	[0.057]	[0.216]	[0.073]	[0.370]	[0.143]	[0.223]	[0.000]	[0.006]	[0.054]	[0.897]
Tomatoes	−0.171	−0.015	−0.031	0.001	−0.011	−0.118	0.011	0.186*	0.027	−0.111*	−0.080*	−0.142*	−0.293*	−0.084
	(−0.421)	(−0.076)	(−0.211)	(−0.039)	(−0.041)	(−0.242)	(−0.032)	(0.108)	(−0.083)	(−0.181)	(−0.128)	(−0.191)	(−0.380)	(−0.276)
	[0.052]	[0.049]	[0.150]	[0.039]	[0.018]	[0.008]	[0.053]	[0.282]	[0.139]	[−0.048]	[−0.025]	[−0.099]	[−0.217]	[0.125]
Other	−0.188*	0.009	−0.283*	−0.031*	0.022	0.032	−0.024	0.103*	−0.109*	0.014	−0.148*	−0.125*	−0.185*	0.099
	(−0.380)	(−0.036)	(−0.415)	(−0.060)	(−0.001)	(−0.057)	(−0.058)	(0.034)	(−0.193)	(−0.034)	(−0.189)	(−0.165)	(−0.242)	(−0.048)
	[−0.035]	[0.058]	[−0.135]	[−0.002]	[0.043]	[0.125]	[0.014]	[0.167]	[−0.033]	[0.067]	[−0.108]	[−0.089]	[−0.123]	[0.254]
Conventional vegetables														
Carrots	0.034	0.024*	0.266*	0.029*	0.015*	0.055*	−0.011	0.027*	0.006	−0.009	0.010	0.034*	−0.014	−0.053
	(−0.043)	(0.006)	(0.218)	(0.018)	(0.007)	(0.019)	(−0.024)	(0.000)	(−0.030)	(−0.030)	(−0.006)	(0.024)	(−0.042)	(−0.123)
	[0.098]	[0.042]	[0.321]	[0.042]	[0.023]	[0.091]	[0.003]	[0.057]	[0.038]	[0.012]	[0.027]	[0.046]	[0.010]	[0.019]
Onions	−0.027	−0.010	−0.127*	−0.031*	−0.005	−0.036*	0.012*	−0.046*	0.030*	−0.004	−0.005	0.014*	0.059*	0.008
	(−0.091)	(−0.027)	(−0.178)	(−0.043)	(−0.014)	(−0.068)	(0.002)	(−0.075)	(0.001)	(−0.022)	(−0.020)	(0.003)	(0.040)	(−0.054)
	[0.032]	[0.007]	[−0.081]	[−0.018]	[0.004]	[−0.006]	[0.023]	[−0.021]	[0.058]	[0.014]	[0.009]	[0.026]	[0.080]	[0.071]
Peppers	−0.042	0.013	−0.048	−0.009	0.018*	0.048*	−0.011	0.054*	−0.004	−0.030*	0.044*	0.029*	0.038*	0.039
	(−0.129)	(−0.008)	(−0.116)	(−0.025)	(0.007)	(0.003)	(−0.027)	(0.022)	(−0.048)	(−0.053)	(0.027)	(0.014)	(0.005)	(−0.044)
	[0.042]	[0.038]	[0.017]	[0.006]	[0.028]	[0.093]	[0.004]	[0.085]	[0.034]	[−0.003]	[0.063]	[0.045]	[0.069]	[0.125]
Potatoes	0.170*	−0.011	0.038	−0.009	0.009*	0.046*	0.027*	−0.111*	0.048*	−0.015	0.044*	0.039*	0.111*	−0.089*
	(0.116)	(−0.024)	(−0.008)	(−0.021)	(0.001)	(0.015)	(0.018)	(−0.134)	(0.018)	(−0.033)	(0.030)	(0.028)	(0.094)	(−0.145)
	[0.233]	[0.005]	[0.088]	[0.004]	[0.017]	[0.076]	[0.035]	[−0.083]	[0.074]	[0.001]	[0.056]	[0.048]	[0.133]	[−0.034]

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Table 5 (*Continued*)

	Household size	Child	White	Other race	Age ≤40	Age 41–64	High school	College	Married	Unemployed	East	Central	South	Urban
Tomatoes	0.011	−0.023*	0.053*	0.017*	−0.015*	−0.039*	−0.011	−0.006	−0.005	0.014	0.005	−0.004	0.017	0.099*
	(−0.058)	(−0.041)	(0.007)	(0.007)	(−0.024)	(−0.071)	(−0.022)	(−0.028)	(−0.039)	(−0.004)	(−0.009)	(−0.017)	(−0.002)	(0.043)
	[0.075]	[−0.006]	[0.096]	[0.028]	[−0.006]	[−0.007]	[0.000]	[0.019]	[0.025]	[0.031]	[0.017]	[0.006]	[0.039]	[0.159]
Other	−0.059*	0.005	−0.061*	−0.001	−0.007*	−0.018*	−0.009*	0.023*	−0.030*	0.007	−0.017*	−0.025*	−0.064*	−0.004
	(−0.086)	(−0.003)	(−0.084)	(−0.006)	(−0.010)	(−0.034)	(−0.016)	(0.012)	(−0.047)	(−0.003)	(−0.023)	(−0.031)	(−0.076)	(−0.032)
	[−0.026]	[0.012]	[−0.035]	[0.004]	[−0.002]	[−0.003]	[−0.004]	[0.034]	[−0.015]	[0.015]	[−0.010]	[−0.018]	[−0.053]	[0.025]

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magnitudes (elasticities ≤0.07). The presence of children increases consumption of organic food in Denmark (Wier *et al*. 2008) and organic fruit and vegetables in the USA (Smith *et al*. 2009). Relative to blacks, white households on average consume more organic carrots but less organic onions, potatoes and other vegetables; they also consume more conventional carrots and tomatoes but less conventional onions and other conventional vegetables.

Compared to elderly households (age ≥65), households headed by individuals age ≤40 consume more of most organic and conventional vegetables except conventional tomatoes and other conventional vegetables; whilst households headed by a 41–64 year old consume more organic carrots but less organic tomatoes, more conventional carrots, peppers and potatoes, but less conventional onions, tomatoes and others. Age increases the consumption of organic food in Denmark and UK (Wier *et al*. 2008) and organic fruit and vegetables in the USA (Smith *et al*. 2009), but decreases the consumption of organic olive oil in Greece (Tsakiridou *et al*. 2006).

College-educated households consume more of all organic vegetables except onions, more conventional carrots, peppers, other conventional vegetables, but less conventional onions and potatoes. Positive effect of education was found for organic olive oil in Greece (Tsakiridou *et al*. 2006), organic food in Denmark (Wier *et al*. 2008) and organic fruit and vegetables in the USA (Smith *et al*. 2009).

Marital status plays a role, with husband–wife households consuming more organic carrots, onions and potatoes, but less of other vegetables, organic or conventional. Households with an unemployed female head consume less conventional peppers but more of other conventional vegetables.

Regional differences are also evident. Relative to those in the West, households in the Eastern, Central, and Southern regions consume less of most organic vegetables. Regional effects are mixed for conventional vegetables, with households in the East consuming more conventional peppers and potatoes but less of other conventional vegetables. Smith *et al*. (2009) also find higher consumption of organic fruit and vegetables amongst households in the West. The role of urbanisation is also noticeable, echoing the positive effects on organic vegetables reported by Smith *et al*. (2009). In sum, after controlling for prices and total expenditure, socio-demographic characteristics are found to play a role in the consumption of organic and conventional vegetables. These results justify inclusion of the household demographic characteristics in accommodating heterogeneity of preference.

6. Concluding remarks

One challenging task in demand analysis with microdata is censoring in the dependent variables. Statistical procedures not accounting for such data feature produce biased and inconsistent estimates. Interest in improving statistical efficiency and the need to impose cross-equation restrictions call for estimation of a censored demand system. Estimation of a large equation

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system with censored dependent variables has remained difficult even with simulation techniques and modern computers. The Bayesian MCMC method offers a practical solution to this difficult problem. By augmenting the latent data with Gibbs sampling, the problem becomes as manageable as in conventional SUR. Applying the Bayesian MCMC technique, we estimate a large LAIDS of organic and conventional vegetables.

Demands are found to be elastic for all organic vegetables but inelastic for all conventional vegetables except potatoes. Expenditure elasticities for organic vegetables are also higher than the corresponding conventional vegetables. Gross substitution and complementarity are both found, whilst net substitution is the dominant pattern.

On demographic characteristics, our results are in agreement with the socio-demographic profile of conventional vegetable consumers depicted in the literature. The effects of these household characteristics highlight the importance of these variables in accommodating heterogeneous preferences.

The implications of our findings for marketing campaigns, nutrition education and policy interventions are obvious. Demand for organic vegetables is very elastic, which suggest price campaigns are likely to be an effective means of promoting consumption. The US Federal government has promoted consumption of more healthy foods including vegetables (USDA-USDHHS 2010). The large expenditure elasticities we find suggest income support programs, such as the Supplemental Nutrition Assistance Program (SNAP) (Lin *et al*. 2010), can be effective in promoting vegetable consumption. Organic producers and retailers may also target promotions towards well-educated households that are more apt to consume organic vegetables. Identifying and educating market segments whose profile does not match the profile of profitable customer groups is also important. For instance, educating African Americans and households residing in the South on the benefits of organic vegetables (e.g. the absence of fertilizers and pesticides, environment safety, better taste) is a crucial marketing strategy.

The Tobit mechanism (Eqn 2) is sometimes considered undesirable because 'any variable which increases the probability of a non-zero value must also increase the mean of the positive values' (Lin and Schmidt 1984, p. 174). Whilst alternative behavioural motivations such as the sample-selection (Yen and Lin 2006) and infrequency-of-purchase (Tiffin and Arnoult 2010) systems are possible, these approaches are *not* feasible for the current application because the number of parameters would also have increased exponentially in such systems. Second, whilst our parsimonious approach to the adding-up restriction produces robust elasticity estimates with respect to the equation deleted in estimation, further studies might address the adding-up restriction more rigorously. Finally, the joint normality assumption of the error terms is not strictly consistent with specification of the share system. Further studies might more carefully address such error-distributional issue.

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References

Albert, J. and Chib, S. (1993). Bayesian analysis of binary and polychotomous response data, *Journal of the American Statistical Association* 88, 669–679.

Amemiya, T. (1974). Multivariate regression and simultaneous equation models when the dependent variables are truncated normal, *Econometrica* 42(6), 999–1012.

Bundesministerium für Ernährung, Landwirtschaft und Verbraucherschutz (BMELV) (Federal Ministry of Food, Agriculture and Consumer Protection) (2011). Organic farming in Germany. Available from URL: http://www.bmelv.de/SharedDocs/Standardartikel/EN/Agriculture/OrganicFarming/OrganicFarmingInGermany.html#doc381512bodyText12 [accessed 12 July 2011].

Chen, M., Shao, Q. and Ibrahim, J. (2000). *Monte Carlo Methods in Bayesian Computation*. Springer-Verlag, New York.

Chib, S. (1992). Bayes inference in the Tobit censored regression model, *Journal of Econometrics* 51(1–2), 79–99.

Deaton, A. and Muellbauer, J. (1980). An almost ideal demand system, *American Economic Review* 70(3), 312–326.

Einav, L., Leibtag, E. and Nevo, A. (2008). On the accuracy of Nielsen Homescan Data, *Economic Research Report No. 69*, Economic Research Service of the U.S. Department of Agriculture (ERS/USDA), Washington, DC.

Geweke, J. (1992). Evaluating the accuracy of sampling-based approaches to the calculation of posterior moments, in Bernardo, J.M., Berger, J., Dawid, A.P. and Smith, A.F.M. (eds), *Bayesian Statistics 4*. Clarendon Press, Oxford, pp. 641–649.

Geweke, J. (2005). *Contemporary Bayesian Econometrics and Statistics*. Wiley, New York.

Glaser, L.K. and Thompson, G.D. (1999). Demand for organic and conventional frozen vegetables, presented at the AAEA Annual Meeting, Nashville.

Glaser, L.K. and Thompson, G.D. (2000). Demand for organic and conventional beverage milk, presented at the WAEA Annual Meeting, Vancouver.

Gracia, A. and de Magistris, T. (2008). The demand for organic foods in the South of Italy: a discrete choice model, *Food Policy* 33(5), 386–396.

von Haefen, R.H., Phaneuf, D.J. and Parsons, G.R. (2004). Estimation and welfare analysis with large demand systems, *Journal of Business and Economic Statistics* 22(2), 194–205.

Huang, H.C. (2001). Bayesian analysis of the SUR Tobit model, *Applied Economics Letters* 8(9), 617–622.

Kasteridis, P., Yen, S.T. and Fang, C. (2011). Bayesian estimation of censored linear almost ideal demand system: food demand in Pakistan, *American Journal of Agricultural Economics* 93(5), 1374–1390.

Kuhar, A. and Juvancic, L. (2010). Determinants of purchasing behaviour for organic and integrated fruits and vegetables in Slovenia, *Agricultural Economics Review* 11(2), 70–83.

Lee, L.-F. and Pitt, M.M. (1986). Microeconometric demand systems with binding non-negativity constraints: the dual approach, *Econometrica* 54(5), 1237–1242.

Lin, T.F. and Schmidt, P. (1984). A test of the Tobit specification against an alternative suggested by Cragg, *Review of Economics and Statistics* 66(1), 174–177.

Lin, B., Yen, S.T., Huang, C.L. and Smith, T.A. (2009). U.S. demand for organic and conventional fresh fruits: the roles of income and price, *Sustainability* 1(3), 464–478.

Lin, B., Yen, S.T., Dong, D. and Smallwood, D.M. (2010). Economic incentives in dietary improvement among food stamp recipients, *Contemporary Economic Policy* 28(4), 524–536.

Millimet, D. and Tchernis, R. (2008). Estimating high-dimensional demand systems in the presence of many binding non-negativity constraints, *Journal of Econometrics* 147(2), 384–395.

Moschini, G. (1995). Units of measurement and the stone index in demand system estimation, *American Journal of Agricultural Economics* 77(1), 63–68.

Nutrition Business Journal. (2007). *U.S. Organic Food Sales ($ mil.) 1997–2010e, Chart 22*. Penton Media, Inc., Cleveland, OH.

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Phaneuf, D.J., Carbone, J.C. and Herriges, J.A. (2009). Non-price equilibria for non-marketed goods, *Journal of Environmental Economics and Management* 57(1), 45–64.

Pudney, S.E. (1989). *Modelling Individual Choice: The Econometrics of Corners, Kinks, and Holes*. Blackwell Publishers, Cambridge, UK.

Smith, T.A., Huang, C.L. and Lin, B. (2009). Does price or income affect organic choice? Analysis of U.S fresh produce users, *Journal of Agricultural and Applied Economics* 41(3), 731–744.

van Soest, A., Kapteyn, A. and Kooreman, P. (1993). Coherency and regularity of demand systems with equality and inequality constraints, *Journal of Econometrics* 57(1–3), 161–188.

Tanner, M.A. and Wong, W.H. (1987). The calculation of posterior distributions by data augmentation, *Journal of the American Statistical Association* 82, 528–549.

Thompson, G.D. and Glaser, L.K. (2001). Demand for organic and conventional baby food, presented at the WAEA Annual Meeting, Logan.

Thompson, G.D. and Kidwell, J. (1998). Explaining the choice of organic produce: cosmetic defects, prices, and consumer preferences, *American Journal of Agricultural Economics* 80(2), 277–287.

Tiffin, R. and Arnoult, M. (2010). The demand for a healthy diet: estimating the almost ideal demand system with infrequency of purchase, *European Review of Agricultural Economics* 37(4), 501–521.

Torjusen, H., Lieblein, G., Wandel, M. and Francis, C.A. (2001). Food system orientation and quality perception among consumers' and producers of organic food in Hedmark County, *Norway, Food Quality and Preference* 12(3), 207–216.

Tsakiridou, E., Konstantinos, M. and Tzimitra-Kalogianni, I. (2006). The influence of consumer's characteristics and attitudes on the demand for organic olive oil, *Journal of International Food & Agribusiness Marketing* 18(3–4), 23–31.

U.S. Department of Agriculture and U.S. Department of Health and Human Services (USDA-USDHHS). (2010). Dietary Guidelines for Americans, Washington, DC. Available from URL: Available from http://www.health.gov/dietaryguidelines/dga2010/DietaryGuidelines2010.pdf [accessed 18 July 2011].

Verhoef, P.C. (2005). Explaining purchases of organic meat by Dutch consumers, *European Review of Agricultural Economics* 32(2), 245–267.

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

Wier, M., Jensen, K.O., Andersen, L.M. and Millock, K. (2008). The character of demand in mature organic food markets: Great Britain and Denmark compared, *Food Policy* 33(5), 406–421.

Willer, H. and Lukas, K. (eds) (2010). *The World of Organic Agriculture – Statistics and Emerging Trends 2010*. International Federation of Organic Agriculture Movements (IFOAM), Bonn and Research Institute of Organic Agriculture (FiBL), Frick. Available from URL: http://www.ifoam.org/pdfs/World_of_OA_Teaser.pdf [accessed 12 July 2011].

Woodland, A.D. (1979). Stochastic specification and the estimation of share equations, *Journal of Econometrics* 10(3), 361–383.

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

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

Yiridoe, E.K., Bonti-Ankomah, S. and Martin, R.C. (2005). Comparison of consumer perceptions and preference toward organic versus conventionally produced foods: a review and update of the literature, *Renewable Agriculture and Food Systems* 20(4), 193–205.

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Supporting Information

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

Data S1. MCMC algorithm, data matrix, diagnostic graphs, and additional tables.

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