Demand for Organic and Conventional Fresh Fruits

Biing-Hwan Lin
Economic Research Service
US Department of Agriculture
e-mail: blin@ers.usda.gov

Steven T. Yen
Department of Agricultural Economics
The University of Tennessee
e-mail: syen@utk.edu

Chung L. Huang
Department of Agricultural and Applied Economics
University of Georgia
e-mail: chuang@uga.edu

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Abstract

We examine consumer demand for organic and conventional fruits by estimating a censored demand system, using Nielsen's Homescan data. Sociodemographic characteristics and income are found to be significant factors of organic fruit consumption. Consumers are responsive to own-price changes in selected organic fruits, while the own-price elasticities for conventional fruits are much smaller. Asymmetric cross-price effects are found between organic and conventional fruits, suggesting that a change in relative prices will more likely cause consumers of conventional fruits to "cross-over" to organic fruits, while the reverse is less likely to happen such that organic consumers will "revert" to conventional fruits.

Keywords: organic fruit, Homescan data, censored demand system, two-step estimation.

Introduction

The US market for organic foods has grown rapidly in the past decade. In 2000, conventional supermarkets for the first time sold more organic food than any other venues (Dimitri and Greene, 2002). Organic food sales rose from $3.6 billion in 1997 to $16.7 billion in 2006, growing at annual rates of 15-21 percent (OTA, 2007). According to OTA, the 2007 organic food sales would exceed $20 billion, and future growth would be at 18 percent a year between 2007 and 2010.

Among the organic food categories, fruit and vegetables by far comprise the largest retail sales, accounting for 40 percent of total organic food sales in 2006. The importance of fruits and vegetables in the organic food markets is also reflected in the production statistics, showing that only 0.2 percent of US corn and soybean acreage was certified organic in 2005, compared with

2.5 percent of fruits and 5 percent of vegetables (USDA-ERS, 2008). Dimitri and Greene (2002) estimated that between 1997 and 2001, US farmers and ranchers nearly doubled the acreage of certified organic land, totaling 2.3 million acres.

Organic products are credence goods—consumers do not know whether a product is organic unless told (Giannakas, 2002). The US Department of Agriculture's (USDA) standards for organic foods, implemented in October 2002, aim at boosting consumer confidence in the organic label and, hence, facilitating further growth in the organic food industry. Krystallis *et al.* (2006) demonstrated that the use of the organic label by farmers, agricultural firms and food companies can be an effective marketing strategy. Their study suggests that an organic label transforms its quality characteristics from credence to search and makes a product more easily accepted by consumers.

Consumer preference for organic food based on perceived desirable attributes and characteristics has been widely documented (Yiridoe et al., 2005). Many studies (Gil *et al*., 2000; Magnusson *et al*., 2001; Roitner-Schobesberger *et al*., 2008; Tsakiridou *et al*., 2008) have shown that there is a widespread belief that organic food is substantially healthier and safer than conventional food, and those notions are fundamental for consumers' purchasing of and their willingness to pay significant price premiums for organics. However, empirical analyses of consumer demand for organic foods are almost nonexistence and few studies have estimated and reported demand elasticities for organic foods (Glaser and Thompson, 1998, 2000). In his review of organic demand literature, Thompson (1998) concluded that "Attitudes, motives, and willingness to pay for organic products have been measured, but apparently no retail data have been available to estimate own-price, cross-price, and income elasticities." The study fills this research void by using the 2006 Nielsen Homescan data to estimate a system of 12 demand equations for 6 categories of organic and conventional fresh fruits.

Even though organic food sector has experienced rapid growth and has made inroad into mainstream supermarkets, organic food sales were estimated to account for about 3 percent of total food sales in the US in 2006 (OTA, 2007). The majority of US consumers do not consume organic food, hence organic demand is characterized by a large portion of observations with zero consumption. This censoring in data is accommodated by using a two-step estimation procedure for consumer demand systems.

Data and Sample

The Nielsen Homescan panel consists of representative US households that provide food purchase data for at-home consumption. In 2006, the panel included 7,534 households, who reported purchases of food products sold as random weight or with the Uniform Product Code (UPC) at retail outlets. For UPC-coded food products, organic produce can be identified by the presence of the USDA organic seal or organic claims created by Nielsen. For random-weight items, Nielsen uses a coding system which identifies organic produce. Homescan panelists do not report prices paid for each food item; they report total quantity purchased and amount paid for that quantity. Therefore, the price is represented by unit value, which is derived by dividing total expenditure, net of any promotional and sale discounts, by the quantity purchased. The Homescan data also include product characteristics and promotion information, as well as detailed socio-demographic information of each household.

For this study, household purchase records of fresh produce, in general reported weekly, were aggregated to the annual level. Among the 7,534 panelists, 7,237 participated at least 10 months in 2006. After deleting observations with missing information on important variables and observations with outliers such as those with extreme values in prices (i.e., 6 standard deviations from the sample mean of each price), a final sample of 6,696 observations was used in this study. Major conventional and organic fresh fruits were identified in this study. Specifically, the demand system includes equations for 12 fruit categories—5 major conventional and 5 major organic fruits (apples, bananas, grapes, oranges, and strawberry) and a catch-all category for other conventional fruits and for other organic fruits. As shown in Table 1, the sample contains large proportions of households who did not purchase organic produce. The proportions of consuming households are relatively small for organic fruits: oranges (2.8%), grapes (3.2%), strawberry (3.8%), apples (8.2%), bananas (11.1%), and other organic fruits (12.1%). The proportions of consuming households are much higher for conventional fruits, ranging from 68.2% for oranges to 93.1% for other fruits. Note that only fresh fruits were included in this study.

Demand System Specification and Econometric Procedure

Our empirical analysis is based on the assumption that organic and conventional fruits are separable from all other consumer goods. We use the Translog demand system (Christensen *et al*., 1975) for n fruit products, in expenditure shares (s_i) form:

$$s_i = (\alpha_i + \Sigma_{j=1}^{n} \beta_{ij} \log v_j) / D, \ i = 1, ..., n, \tag{1}$$

where v_1, ..., v_n are expenditure-normalized prices, and $D = \Sigma_{j=1}^{n} \alpha_j + \Sigma_{k=1}^{n} \Sigma_{j=1}^{n} \beta_{kj} \log v_j$ which is the sum of the numerator in equation (1), with the restriction that $\Sigma_{j=1}^{n} \alpha_j = 1.$ This demand system is derived from the Translog indirect utility function which is second-order approximation to any functional forms. Homogeneity is implied in equation (1), and the symmetry restrictions

$$\beta_{ij} = \beta_{ji} \ \forall \ i, j \tag{2}$$

are also imposed. Household characteristics are incorporated in equation (1) by specifying parameters α_i as functions of demographic variables h_ℓ $(\ell = 1,..., L)$

$$\alpha_i = \alpha_{i0} + \Sigma_{\ell=1}^{L} \alpha_{i\ell} h_\ell,\ i = 1,..., n-1, \tag{3}$$

where α_{i0} and $\alpha_{i\ell}$ are parameters to be estimated. Such demographic specifications for the $n-1$ equations (only) are explained below. The linear demographic specification was also followed in other studies with the Translog demand system (e.g., Yen *et al*., 2003) and the linear approximate almost ideal demand system (e.g., Salvanes and DeVoretz, 1997).

As noted above, the sample contains a large proportion of households who did not purchase certain fruit products during the sample period. Such censoring of the expenditures has to be accommodated to obtain consistent estimates of demand parameters and elasticities. While a number of maximum-likelihood (ML) estimators are available in the literature (e.g., Lee and Pitt, 1986; Wales and Woodland, 1983; Yen *et al*., 2003; Yen and Lin, 2006), the large demand system with many zeros makes ML estimation computationally difficult, with nearly 85% of the sample calling for 6 or higher-level integration of the normal probability density. The two-step censored system estimator (Shonkwiler and Yen, 1999), more formally motivated with a multivariate sample selection model (Yen and Lin, 2006), provides a practical solution to the problem.

Let $x = [\log v_1,..., \log v_n, h_1,..., h_L)'$ be a vector of explanatory variables and θ a vector containing all parameters (α's and β's), and consider an n-equation system in which each expenditure share w_i is generated by a deterministic function $f_i(x; \theta)$ constituting the RHS of the share equation (1), and an unobservable error term e_i. Each equation is subject to the sample selection rule (cf. Heckman, 1979)

$$w_i = d_i[f_i(x;\theta) + e_i],\ i = 1,..., n, \tag{4}$$

such that each indicator d_i is modeled with a binary probit

$$d_i = 1(z'\gamma_i + u_i > 0),\ \ i = 1,\ldots,n, \tag{5}$$

where $1(A)$ denotes the indicator function, taking a value 1 if event A holds, and 0 otherwise, z is a vector of variables, γ_i is a vector of parameters, and u_i is idiosyncratic error distributed as standard normal $N(0,1)$.

The expenditure shares in equation (4) do not add up to unity unless $d_1 = \ldots = d_n = 1$, that is, when none of the dependent variables are subject to sample selection. We follow the simple approach suggested in Yen and Lin (2006), by estimating the first $n - 1$ equations with the nth good treated as a residual category (cf. Pudney, 1989). The resulting estimates are not invariant with respect to the equation excluded. Yen and Lin (2006) however demonstrated in an application to food consumption in China that excluding alternative equations from the system did not cause discernable differences in the elasticity estimates.

Assuming the concatenated error vector $[u_1,\ldots,u_{n-1},e_1,\ldots,e_{n-1}]'$ is distributed as $(2n–2)$-dimensioned normal distribution with zero means and a finite covariance matrix with elements $\sigma_{ij}\ (i, j = 1,\ldots,2n-2),$ the sample selection model can be estimated with the ML procedure (Yen and Lin, 2006). However, with a large system of $n = 12$ equations, the ML procedure would require estimation of a much larger number of parameters than the two-step procedure and evaluations of 11-level probability integrals for all sample observations which is not feasible (even with a simulation estimation procedure) with the large sample size for the current application.[1] A practical alternative is to estimate the system with a two-step procedure, motivated by the unconditional mean of the expenditure shares

$$E(w_i) = \Phi(z_i'\gamma_i) f_i(x;\theta) + \sigma_{(n-1+i),i}\phi(z_i\gamma_i),\ \ i = 1,\ldots,n-1, \tag{6}$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ are univariate standard normal probability density and cumulative distribution functions, respectively, and $\sigma_{(n-1+i),i}$ is the covariance between the error terms (u_i, e_i) of the ith selection and level equations. The unconditional means (6) follow from the bivariate normality of the error terms (u_i, e_i) for i = 1,..., n–1, and suggest a two-step estimation procedure which, as initially suggested in Shonkwiler and Yen (1999) for a linear system, consists of two steps: (i) a probit estimation based on a binary outcome for $d_i = 1(w_i > 0)$ to obtain ML estimates $\hat{\gamma}_i$ for each i; and (ii) estimation of the augmented nonlinear system

$$w_i = \Phi(z_i'\hat{\gamma}_i) f_i(x;\theta) + \sigma_{(n-1+i),i}\phi(z_i'\hat{\gamma}_i) + \xi_i,\ \ i = 1,\ldots,n-1 \tag{7}$$

with ML or a method of moments procedure such as the iterated seemingly unrelated regression, where ξ_i is a composite and heteroscedastic error term, and $\sigma_{(n-1+i),i}$ are additional parameters to estimate (in addition to θ). This two-step procedure is less efficient than the ML procedure in Yen and Lin (2006) but produces statistically consistent estimates for θ and $\sigma_{(n-1+i),i}$. Demand elasticities for the first (n – 1) goods can be derived by differentiating the unconditional means (6), and elasticities for the nth good by using the adding-up restriction (Yen *et al.*, 2003, Footnote 9).

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[1]In the current application we estimate n – 1 = 11 equations, all of which subject to sample selection, which requires estimation of a 22 × 22 covariance matrix with 253 elements.

Results

The Translog demand system of 11 equations was estimated with the two-step procedure described above. With such a large demand system, we needed to pay special attention to the inclusion of demographic variables because the number of parameters is an exponential function of explanatory variables. Therefore, we included most of the socio-demographic variables in the first step (probit) estimation, and minimized the number of parameters by using only two demographic variables in the second step. The definitions and sample statistics of demographic variables included in the empirical analysis are presented in Table 2. Variables used in the first step included income, household size, and dummy variables indicating presence of children, race and ethnicity (white, black, Hispanic, oriental, and other race), region (East, Central, South, and West), urbanization (urban and rural), marriage status of household head (married or not), employment status of the female head (employed or not), and education (no college, some college, and college degree). The demand system incorporated only two dummy variables indicating age of the household head (age 40–64 and age ≥ 65). Note that the Translog demand system includes expenditure on the 12 categories of fresh fruits. The expenditure is expected to increase with income, even though we did not examine the relationship between income and expenditure on fresh fruits.

Table 3 presents the probit results obtained from the first-step estimation. As typical with cross sectional data, goodness-of-fit measures are low for the probit analysis, with McFadden's R^2 ranging from 1% for organic grapes to 3.8% for conventional apples. However, percentage of correct predictions, at a probability cut-off of 0.5 (Wooldridge, 2002: 465), are all greater than 65%, ranging from 68.2% for conventional oranges to 97.2% for organic oranges.

Many of the socio-demographic variables did not have any significant impacts on the probabilities of purchasing fresh fruits in general. However, household income, education, household size, region, marital, and employment status are important variables that influence significantly the probabilities of purchasing fresh fruits. Specifically, household income is found to have significant positive impacts on the purchases of fresh fruits, particularly on both organic and conventional apples and strawberry, and other organic fruits. With respect to education, households with at least some college education (of the household head) are more likely to purchase organic fruits than those households with only high school or less than high school education. Household size also shows a significant positive effect on the likelihood of purchasing conventional grapes, oranges and strawberry. Married households are more likely to purchase organic bananas and all conventional fruits than their counterparts. Similarly, households with unemployed female household head are found more likely to purchase conventional fruits and some organic fruits, including apples, bananas, strawberry and other organic fruits. Households residing in the Western region of the US are more likely to purchase fresh fruits than households in other regions. This is especially true with respect to purchases of organic fruits, except for households in the Central region which appear to be more likely to purchase conventional apples, grapes, oranges and strawberry than households residing in other regions.

The second-step estimates for the Translog demand system suggest that age of household head plays a role in buying fresh conventional fruits, but does not affect the purchase of organic fruits. The second-step estimates are not presented due to space consideration but are available upon request. Nearly one-half (38) of the 78 coefficients for the quadratic price terms (β_{ij}) are statistically significant at the 5% level or lower, and three more are significant at the 10% significance level. The selectivity terms are not significant for organic oranges, organic bananas, and conventional apples but significant for all other equations (at the 10% significance level or lower), suggesting the importance of accommodating zero observations. In what follows, we focus primarily on the demand elasticities derived from the estimation of the Translog system instead of the parameter estimates.

Demand Elasticities

The uncompensated price and expenditure elasticities computed from the estimated Translog demand system are presented in Table 4. All expenditure elasticities are positive and significant at the 1% probability level, ranging from 0.81 for organic bananas to 1.03 for organic oranges and from 0.98 for conventional bananas to 1.01 for other major conventional fruits. The results show that the expenditure elasticities for organic and conventional fruits tend to be unitary, implying that given an increase in the spending on the selected fresh fruits, consumers would allocate approximately the same proportion of increase in their purchase of conventional and organic fresh fruits. Our expenditure estimates are quite similar to those reported by Glaser and Thompson (1998), who reported elasticities ranging from 0.778 for organic frozen corn to 1.489 for organic green peas and from 0.892 for conventional frozen green peas to 1.158 for conventional frozen corn.

There appears to be a widely held belief in the organic trade circle that household income is not correlated with expenditures on organic food. Thus, some popular presses have suggested that lower income families may choose to buy organic when possible as a means of preventative medicine, and they are at least as likely to purchase organic as other income groups (Hartman Group, 2003; OTA, 2004). A simple cross-tabular analysis of spending on organic produce by household income class also seems to support the commonly held belief (Stevens-Garmon *et al.*, 2007). Thus, income has not been tracked in monitoring organic trade (Fromartz, 2006). Our finding of positive and statistically significant expenditure elasticities strongly suggest that demands for fresh organic fruits rise with income—a result that seems at odds with the conventional wisdom in the organic trade.

All own-price elasticities are negative and statistically significant at the 1% significance level, except for organic oranges, organic strawberry, and other organic fruits. Among those with significant own-price elasticities, demands for organic fruits are found to be price elastic, whereas demands for conventional fruits are price inelastic. Our estimates of organic own-price elasticities range from –1.06 for apples to –3.19 for bananas and –3.54 for grapes. The finding of a highly elastic demand for organic fruits is to be expected because organic produce typically commands a price premium (Lin *et al*., 2008) with a small market share. The result implies that the demands for organic fruits are price sensitive, suggesting that a 1% change in the prices will elicit more than 1% change in quantities demanded. Empirical studies that report price elasticities for organic foods are far and between. Glaser and Thompson (1998) reported own-price elasticities for four organic frozen vegetables (broccoli, corn, green peas, and green beans) ranging from –1.630 to –2.268. Demands for organic milk were found to be highly responsive to own-price changes with elasticities ranging from –3.637 for whole fat milk to –9.733 for 1% fat milk (Glaser and Thompson, 2000).

Our estimates of own-price elasticity for conventional fresh fruits are –0.49 (grapes), –0.50 (strawberry), –0.57 (oranges), –0.70 (bananas), –0.83 (apples), and –0.85 (other fruits). In a recent study of demands for conventional fresh fruits, Brown and Lee (2002) reported similar elasticities of –0.52 for apples, –0.54 for bananas, –0.56 for grapes, and –0.67 for oranges. In an early study of demands for fresh fruits, George and King (1971) reported own-price elasticities of –0.72 for apples, –0.61 for bananas, –0.65 for oranges, and –0.60 for other fruits.

Among the 66 pairs of cross-price elasticities estimated for organic and conventional fruits, we found about half of them, or 34 pairs, are statistically significant at the 10% significance level or lower. Complementary relationships are also found to be dominant between most organic and conventional fruits. Among the six organic fruits, there are 8 significant positive and 10 significant negative cross-price elasticities. In contrast, the results show that almost all conventional fruits are gross complements to each other; only conventional strawberry is found to have a significant substitution relationship with other conventional fruits. As with the own-price elasticities, all conventional fruits are shown to have inelastic cross-price elasticities, while organic cross-price elasticities are larger in magnitudes and more responsive to price changes of other organic fruits.

As shown in Table 4, among the 10 significant cross-price elasticities between organic and conventional fruits, 6 cross-price elasticities are positive and 4 negative. The result shows that consumers tend to increase their purchase of organic fruits, if there is an increase in the prices of conventional fruits. On the other hand, there are 7 positive and 7 negative significant cross-price elasticities between conventional and organic fruits. The results seem to suggest that consumers are more likely to substitute organic fruits for conventional fruits than the other way around. It is noted that among the significant cross-price elasticities, most organic fruits are gross substitutes for conventional fruits whereas organic fruits could be either gross substitutes or complements for conventional fruits. The finding is perhaps to be expected given that organic fruits are priced higher than conventional fruits, making it easier to switch from conventional to organic fruits, if organic fruits become relatively inexpensive when the prices of conventional fruits increase.

In addition, the magnitudes of the cross-price elasticities between conventional and organic fruits in general tend to be larger than those between organic and conventional fruits, suggesting that changes in the prices of conventional fruits will generally induce proportionally larger responses to organic fruits than to conventional fruits as organic prices change. In other words, purchases of organic fruits are more responsive to changes in prices of conventional fruits than changes in purchase of conventional fruits as organic prices change. Although they found only two pairs of significant cross-price elasticities for corn and between organic and conventional broccoli, Glaser and Thompson (1998) also observed a similar asymmetry in cross-price responses. They suggest that this asymmetry would imply that a change in relative prices will more likely cause consumers of conventional fruits to "cross-over" to buy organic fruits, while the reverse is less likely to happen such that organic consumers will "revert" to buy conventional fruits.

Conclusions

The study fills a critical empirical void in the extant literatures pertaining to demands for organic foods. Most previous studies of organic demands have focused on consumer attitudes and willingness to pay for organic foods primarily due to the lack of available retail purchase data. Although the demand for organic foods has grown rapidly, the organic market share at retail level remains relatively small. According to the Nielsen Homescan panel data, the proportion of households that purchase organic fruits in 2006 varies from 2.81% for oranges to 11.14% for bananas (12.08% for the catch-all other fruits). In this study, we examine consumer demand for selected major organic and conventional fruits by estimating a censored demand system. By investigating the interrelationship between consumption of organic and conventional fresh fruits, this study presents the much needed price elasticities for organic fruits as well as those cross-price elasticities between organic and conventional fruits.

Results obtained from this study provide several important market implications to assist producers, retailers and policy-makers in planning future development and growth of organic foods in the US. Our study shows that many socio-demographic characteristics are significant factors in affecting the probability of purchasing organic fruits. Specifically, households in the Western region, married households, and households with unemployed female head, college education and higher income were found to be more likely to buy some kinds of organic fresh fruits than their counterparts.

In addition to the positive effect of income on the likelihood of buying organic fresh fruits, expenditure elasticities for organic fruits are found to be positive and statistically significant. Even though the scope of our study is limited to fresh organic fruits and not the comprehensive organic food sector, the finding of a positive relationship between income and organic demand suggests that simple correlation analysis of the relationship could be misleading. Future study on the issue should be encouraged.

As to be expected, our elasticities measures suggest that consumers are quite sensitive to own-price changes in fresh organic fruits. The organic own-price elasticities are found to be highly elastic ranging from –1.06 to –3.54 as compared to the range of –0.49 to –0.85 for conventional fresh fruits. Our finding that consumers are more responsive to changes in prices of organic fruits than that of conventional fruits is consistent with a previous study which found own-price elasticities for organic frozen vegetables are generally two to three times larger than their conventional counterparts (Glaser and Thompson, 1998).

There are some strong statistical evidences indicating that cross-price effects between organic and conventional fruits are asymmetric. This asymmetry in cross-price elasticities would imply that a change in relative prices more likely will cause consumers of conventional fruits to "cross-over" to buy organic fruits, while the reverse is less likely to happen such that organic consumers will "revert" to buy conventional fruits. Given that organic own-price elasticities are highly elastic and the cross-price elasticities are asymmetric, we would expect that as the price premium on organic fruits drops the demand for organic fruits would continue to grow and expand as more consumers would participate and purchase organic foods.

A few caveats pertain. First, due to the small proportions of consuming households demands were aggregated to the annual level and therefore, some information (such as seasonal variation) is lost during such aggregation. Further studies might consider estimation of the demand system with monthly or weekly data as organic food products become more popular. We also note that, by focusing on organic and conventional fruits the system estimated is a partial demand system. Last but not least, future studies might consider estimation of the demands for a broader group of conventional and organic food products.

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Table 1. Sample statistics: expenditures, expenditure shares, and prices

Variable	% Consuming	Mean	S.D.
Expenditures ($ / year)			
Organic fruits			
Apples (o)		0.78	7.70
Consuming households	8.17	9.58	25.35
Bananas (o)		0.50	3.86
Consuming households	11.14	4.45	10.77
Grapes (o)		0.21	1.93
Consuming households	3.15	6.76	8.65
Oranges (o)		0.16	1.69
Consuming households	2.81	5.84	8.34
Strawberry (o)		0.24	2.23
Consuming households	3.79	6.33	9.65
Other fruits (o)		1.20	9.14
Consuming households	12.08	9.92	24.60
Conventional fruits			
Apples (c)		19.34	30.59
Consuming households	82.69	23.39	32.20
Bananas (c)		16.59	20.70
Consuming households	88.50	18.74	21.07
Grapes (c)		14.70	24.17
Consuming households	74.09	19.84	26.20
Oranges (c)		10.42	19.34
Consuming households	68.18	15.29	21.78
Strawberry (c)		12.31	19.43
Consuming households	69.25	17.78	21.17
Other fruits (c)		47.21	62.97
Consuming households	93.10	50.71	63.89
Expenditure shares			
Apple (o)		0.004	0.028
Bananas (o)		0.005	0.036
Grapes (o)		0.002	0.015

Oranges (o)	0.001	0.019
Strawberry (o)	0.002	0.016
Other fruits (o)	0.008	0.046
Apples (c)	0.154	0.165
Bananas (c)	0.162	0.176
Grapes (c)	0.116	0.137
Oranges (c)	0.083	0.119
Strawberry (c)	0.104	0.140
Other fruits (c)	0.359	0.224
Prices ($ / lb.)		
Apple (o)	1.44	0.22
Bananas (o)	0.61	0.08
Grapes (o)	1.95	0.19
Oranges (o)	0.95	0.13
Strawberry (o)	2.51	0.75
Other fruits (o)	1.41	0.72
Apples (c)	1.08	0.31
Bananas (c)	0.48	0.12
Grapes (c)	1.55	0.47
Oranges (c)	0.93	0.23
Strawberry (c)	2.08	0.58
Other fruits (c)	1.21	0.68
Sample size	6,696	

Source: Compiled from Nielsen's Homescan panel, 2006. Abbreviations "o" and "c" in parentheses indicate organic and conventional fruits, respectively.

Table 2. Definitions and sample statistics of demographic variables

Variable	Definition	Mean	S.D.
Continuous variables			
Household size	Number of members in households	2.33	1.29
Income	Household income as a % of Federal poverty level	421.60	275.59
Binary variable (yes = 1; 0 = no)			
Child	Presence of a child(ren)	0.22	
White	Race is white	0.74	
Black	Race is black	0.13	
Hispanic	Race is Hispanic	0.07	
Oriental	Race is Asian	0.04	
Other race	Race is others (ref.)	0.02	
East	Resides in East region of the country	0.22	
Central	Resides in central region	0.17	
South	Resides in South region	0.38	
West	Resides in South region (ref.)	0.23	
Urban	Resides in an urban area	0.86	
Married	Dual-headed household	0.58	
Unemployed (F)	Female household head unemployed	0.38	
≤ High school	Max. education of head is HS or lower (ref.)	0.18	
Some college	Max. education of head is some college	0.30	
≥ college	Max. education of head is college grad. or higher	0.51	
Age < 40	Oldest head age ≤ 40 (reference)	0.10	
Age 40−64	Oldest head age 41–64	0.61	
Age ≥ 65	Oldest head age ≥ 65	0.29	
Sample size		6,696	

Source: Compiled from Nielsen's Homescan panel, 2006.

Table 3. First-step probit estimates of fruit demands

Variable	Apples (o)	Bananas (o)	Grapes (o)	Oranges (o)	Straw-berry (o)	Other fruits (o)	Apples (c)	Bananas (c)
Constant	–1.530***	–1.406***	–2.198***	–2.109***	–2.152***	–1.308***	0.599***	1.104***
	(0.187)	(0.185)	(0.321)	(0.289)	(0.269)	(0.170)	(0.166)	(0.183)
Child	0.084	–0.029	–0.036	–0.093	–0.007	0.011	0.207***	0.013
	(0.079)	(0.073)	(0.105)	(0.111)	(0.107)	(0.071)	(0.068)	(0.075)
White	–0.198	0.037	0.244	0.009	0.070	–0.172	–0.120	–0.059
	(0.157)	(0.162)	(0.290)	(0.253)	(0.230)	(0.143)	(0.146)	(0.159)
Black	–0.133	0.238	0.384	0.233	0.082	–0.130	–0.280*	–0.214
	(0.167)	(0.169)	(0.298)	(0.263)	(0.241)	(0.152)	(0.152)	(0.165)
Hispanic	–0.048	0.172	0.462	0.195	0.056	–0.052	–0.185	–0.165
	(0.173)	(0.175)	(0.303)	(0.270)	(0.251)	(0.158)	(0.160)	(0.174)
Oriental	–0.136	–0.066	0.458	0.036	0.149	–0.190	–0.249	–0.229
	(0.187)	(0.191)	(0.317)	(0.291)	(0.259)	(0.171)	(0.173)	(0.188)
East	–0.135**	–0.183***	–0.064	–0.058	–0.122	–0.211***	–0.046	–0.168***
	(0.066)	(0.061)	(0.092)	(0.09)	(0.083)	(0.059)	(0.056)	(0.062)
Central	–0.235***	–0.205***	–0.127	–0.191*	–0.185**	–0.282***	0.221***	0.038
	(0.075)	(0.067)	(0.104)	(0.107)	(0.096)	(0.067)	(0.064)	(0.070)
South	–0.181***	–0.203***	–0.049	–0.185**	–0.238***	–0.244***	0.006	–0.078
	(0.059)	(0.054)	(0.081)	(0.084)	(0.076)	(0.052)	(0.050)	(0.057)
Urban	0.099	0.042	0.096	0.026	0.216**	0.111*	–0.042	–0.001
	(0.073)	(0.063)	(0.100)	(0.102)	(0.103)	(0.065)	(0.058)	(0.064)
Married	0.093	0.088*	–0.050	–0.036	–0.049	–0.076	0.353***	0.355***
	(0.057)	(0.052)	(0.075)	(0.079)	(0.074)	(0.051)	(0.046)	(0.052)
Unemployed (F)	0.110**	0.085**	0.021	0.103	0.115*	0.130***	0.225***	0.228***
	(0.048)	(0.044)	(0.066)	(0.069)	(0.063)	(0.044)	(0.041)	(0.046)

Some college	0.165**	0.093	–0.081	–0.092	–0.033	0.148**	0.141***	–0.084
	(0.074)	(0.065)	(0.093)	(0.099)	(0.09)	(0.065)	(0.053)	(0.062)
≥ College	0.282***	0.232***	0.041	0.051	0.181**	0.250***	0.178***	–0.092
	(0.071)	(0.062)	(0.088)	(0.093)	(0.090)	(0.063)	(0.052)	(0.060)
Income × 10^{-2}	0.019**	0.003	–0.009	0.019	0.040***	0.032***	0.015**	0.009
	(0.009)	(0.008)	(0.013)	(0.012)	(0.010)	(0.008)	(0.008)	(0.008)
Household size	–0.022	–0.008	0.036	0.060	–0.019	0.019	0.001	0.012
	(0.029)	(0.027)	(0.037)	(0.038)	(0.040)	(0.026)	(0.024)	(0.027)
Log likelihood	−1,858.423	−2,310.027	−927.847	−843.817	−1,047.225	−2,415.848	−2,966.842	−2,312.651
McFadden's R^2	0.019	0.013	0.010	0.015	0.031	0.021	0.038	0.032
% correct predict	91.80	88.90	96.80	97.20	96.20	87.90	82.70	88.50

Note: Asymptotic standard errors in parentheses. Levels of statistical significance: *** = 1%, ** = 5%, * = 10%.

Table 3 continued.

Variable	Grapes (c)	Oranges (c)	Straw-berry (c)
Constant	0.052	0.209	–0.196
	(0.145)	(0.145)	(0.144)
Child	0.084	0.013	0.046
	(0.061)	(0.058)	(0.060)
White	0.089	–0.156	0.008
	(0.125)	(0.126)	(0.125)
Black	0.156	–0.107	–0.236*
	(0.132)	(0.132)	(0.131)
Hispanic	0.088	–0.064	–0.080
	(0.138)	(0.139)	(0.138)
Oriental	–0.054	–0.047	–0.095
	(0.150)	(0.152)	(0.150)
East	0.040	–0.032	–0.120***
	(0.051)	(0.049)	(0.049)
Central	0.199***	0.145***	0.209***
	(0.056)	(0.054)	(0.055)
South	0.026	–0.099**	0.057
	(0.045)	(0.044)	(0.044)
Urban	0.026	0.008	0.180***
	(0.051)	(0.049)	(0.049)
Married	0.265***	0.188***	0.229***
	(0.042)	(0.041)	(0.041)
Unemployed (F)	0.170***	0.188***	0.149***
	(0.037)	(0.035)	(0.036)

Some college	0.055	0.057	0.077
	(0.050)	(0.048)	(0.048)
≥ College	0.068	0.136***	0.167***
	(0.048)	(0.047)	(0.047)
Income	0.010	0.007	0.017***
	(0.007)	(0.007)	(0.007)
Household size	0.049**	0.053***	0.079***
	(0.023)	(0.021)	(0.022)
Log likelihood	−3,740.826	−4,107.903	−3,996.544
McFadden's R^2	0.024	0.019	0.033
% correct predict	74.10	68.20	69.50

Note: Asymptotic standard errors in parentheses. Levels of statistical significance: *** = 1%, ** = 5%, * = 10%.

Table 4. Uncompensated price and total expenditure elasticities

Product	Apples (o)	Bananas (o)	Grapes (o)	Oranges (o)	Straw-berry (o)	Other fruits (o)	Apples (c)	Bananas (c)
Apples (o)	–1.06***	0.65***	–0.55*	0.07	0.05	0.41***	0.10	–0.46***
Bananas (o)	1.05***	–3.19***	2.72***	–1.51***	0.10	–0.16	–0.20	1.13***
Grapes (o)	–0.65*	1.97***	–3.54***	1.78***	–0.49	–1.13***	0.73***	–0.10
Oranges (o)	0.08	–0.98***	1.66***	–0.92	–0.82*	0.11	–0.32	0.48*
Strawberry (o)	0.06	0.08	–0.50	–0.90**	–0.36	–0.61***	0.69***	0.19
Other fruits (o)	0.32**	–0.07	–0.75***	0.07	–0.39***	–0.01	–0.06	0.04
Apples (c)	0.03	–0.05	0.19***	–0.09	0.18***	–0.02	–0.83***	–0.08**
Bananas (c)	–0.16***	0.23***	–0.03	0.14*	0.05	0.02	–0.08**	–0.70***
Grapes (c)	0.02	–0.13***	0.05	0.05	0.04	–0.06	–0.10***	–0.12***
Oranges (c)	–0.19***	–0.03	0.03	0.03	0.18***	–0.02	–0.12***	–0.10**
Strawberry (c)	0.00	–0.05	0.01	–0.15*	–0.02	–0.11***	–0.13***	–0.09**
Other fruits (c)	0.08***	0.00	–0.10***	0.01	–0.14***	0.04*	0.06***	–0.02

Table 4 continued.

Product	Grapes (c)	Oranges (c)	Straw-berry (c)	Other fruits (c)	Total Expend.
Apples (o)	0.05	–0.40***	0.00	0.16	0.99***
Bananas (o)	–0.53***	–0.10	–0.20	0.08	0.81***
Grapes (o)	0.15	0.08	0.04	0.21	0.97***
Oranges (o)	0.12	0.07	–0.44	–0.07	1.03***
Strawberry (o)	0.13	0.45***	–0.06	–0.18	0.99***
Other fruits (o)	–0.13	–0.03	–0.22***	0.23**	0.99***
Apples (c)	–0.08***	–0.08***	–0.11***	–0.08***	1.01***
Bananas (c)	–0.10***	–0.07**	–0.07**	–0.21***	0.98***
Grapes (c)	–0.49***	–0.10***	–0.08**	–0.09***	1.01***
Oranges (c)	–0.12***	–0.57***	0.00	–0.10***	1.01***
Strawberry (c)	–0.08**	0.00	–0.50***	0.11***	1.01***
Other fruits (c)	–0.03	0.00	–0.04**	–0.85***	1.00***

Note: Asymptotic standard errors in parentheses. Levels of statistical significance: *** = 1%, ** = 5%, * = 10%.