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Article

U.S. Demand for Organic and Conventional Fresh Fruits: The Roles of Income and Price

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Abstract: Using retail purchase data reported by Nielsen's Homescan panel this study investigates the U.S. demand for organic and conventional fresh fruits. The study fills an important research void by estimating the much needed income and price elasticities for organic and conventional fruits utilizing a censored demand approach. Household income is found to affect organic fruit consumption. Consumers are more responsive to price of organic fruits than to price of conventional fruits. Cross-price effects suggest that a change in relative prices will more likely induce consumers to "cross-over" from buying conventional fruits to buying organic fruits, while it is less likely that organic consumers will "revert" to buying conventional fruits.

Keywords: National Organic Standards; Nielsen Homescan; organic fruit demand; price elasticities; censored demand system

1. Introduction

Demand for food and agricultural products increases as our population continues to grow and expand. The world is facing an ever increasing pressure to develop and adopt another green revolution for meeting its food requirements to feed the population without depleting Earth's resources, polluting its environment, or causing irreversible damages to the health of our ecosystem. There are many technologies that have emerged as promising sustainable agriculture practices that could possibly meet expected demand with improved environmental protection. Organic agriculture has been touted and promoted as a farming system that is consistent with the goals of sustainable agriculture and offers many environmental benefits through its management practices that enhance biodiversity, restore and maintain the natural ecological harmony.

Over the past decade, organic food sales grew rapidly from $3.6 billion in 1997 to $18.9 billion in 2007 [1], as they have become increasingly affordable and available in mainstream grocery stores. There is a widespread belief that organic food is substantially healthier and safer than conventional food, and these notions are fundamental for consumers' purchasing of and their willingness to pay price premiums for organics [2-5]. The recent growth in organic sales reflects public concerns over pollution, food safety, health and nutrition, as well as increasing awareness to support a sustainable agricultural system. As a result, organic farming has expanded rapidly bringing additional farmland into production that doubled certified organic land over 2001–2005 from 1.9 to 4.1 million acres [6]. However, marketable yields from organic enterprises are typically lower than what could be realized in conventional farming. Although the increasing shift from production to environmental and social goals favors organic agriculture, the substantial lower organic productivity could be a potential impediment for the industry to achieve a greater economic sustainability. No agriculture is sustainable if it is not also profitable. To that end, American consumers have been willing to pay price premiums of at least 20 to 60 percent for organic produce [7] to help make organic agriculture economically viable.

There is a rich literature on consumer perceptions and preferences toward organic foods [8]. However, few studies have estimated demand elasticities for organic foods [9,10]. In his review of organic demand literature, Thompson [11] 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."

While the empirical literature on organic demand has been lacking, there is a notion in the trade circle that price and income do not necessarily track organic sales [12,13]. Lack of influence exerted by price and income on organic purchases appears to contradict each other. In early development of the organic food market, organic sales concentrated in niche markets, such as natural and specialty food stores, which typically serve higher income consumers [14]. Affluent consumers may place a high value on the health and environmental benefits of organic food and hence willing to pay the premium—price does not matter but income does. As organic foods penetrate into mainstream supermarkets, they become available to a much larger consumer base of less affluent and price conscious customers. As a result of the phenomenal growth in the organic sector during the past decade, the roles of price and income in organic sales may have evolved.

This study is our first attempt to fill this research void by focusing on the demand for organic and conventional fresh fruits. The separation of organic and conventional fruits enables us to test the hypothesis that consumer demand for organic fruits differs from that of conventional fruits. We utilize a censored demand system to address the issue that a majority of consumers do not buy organic fruits. As discussed in the data and method section, the estimation complexity restricts the number of food categories in a censored demand system. Consequently, we specify a demand system with 12 categories of organic and conventional fruits, excluding other food categories such as vegetables. In 2007, fruits and vegetables by far comprised the largest retail sales value, accounting for 37 percent of the total organic food sector ($6.9 billion out of $18.9 billion) [1]. About 92% of the organic produce sector can be attributed to fresh produce [15]. According to the U.S. Bureau of Labor Statistics' Consumer Expenditure Survey, spending on fresh fruits has accounted for 50-52% of total U.S. fresh produce spending over 1997–2007 [16]. It is important to note that the determinants of food demand vary by food sectors. For example, it has been documented that aging tends to decrease the demand for fruits, fried potatoes, and tomatoes but to increase the demand for other vegetables [17]. Such variation is likely to extend into the demand for organics. Therefore, it is important to point out that our findings of the changes in consumers' demand for fresh organic and conventional fruits under different income and price conditions may or may not apply to other organic food sectors.

2. Results and Discussion

Our estimation of fruit demand is based on retail purchase records reported by Nielsen's Homescan panelists in 2006 (see the data section for details). The demand system includes equations for 12 fruit categories—five major conventional and five major organic fruits (apples, bananas, grapes, oranges, and strawberries) and two catch-all categories for other conventional and other organic fruits. The sample contains large proportions of households who did not purchase fresh organic fruits (Table 1).

Table 1. Share of households consuming organic and conventional fruit and mean expenditures.

Fruits	% of Households Consuming	Mean Expenditures: $/year (S.D.)	
		All Households	Consuming Households
Organic			
Apples	8.17	0.78 (7.70)	9.58 (25.35)
Bananas	11.14	0.50 (3.86)	4.45 (10.77)
Grapes	3.15	0.21 (1.93)	6.76 (8.65)
Oranges	2.81	0.16 (1.69)	5.84 (8.34)
Strawberries	3.79	0.24 (2.23)	6.33 (9.65)
Other fruits	12.08	1.20 (9.14)	9.92 (24.60)
Conventional			
Apples	82.69	19.34 (30.59)	23.39 (32.20)
Bananas	88.50	16.59 (20.70)	18.74 (21.07)
Grapes	74.09	14.70 (24.17)	19.84 (26.20)
Oranges	68.18	10.42 (19.34)	15.29 (21.78)
Strawberries	69.25	12.31 (19.43)	17.78 (21.17)
Other fruits	93.10	47.21 (62.97)	50.71 (63.89)
Sample Size	6,696		

Source: Compiled from Nielsen's Homescan Panel, 2006. Notes: Numbers in parentheses are standard deviations.

The proportion of households consuming organic fruits is relatively small: oranges (2.8%), grapes (3.2%), strawberries (3.8%), apples (8.2%), bananas (11.1%), and other organic fruits (12.1%). Consumption of fresh conventional fruits is much higher, ranging from 68.2% for oranges to 93.1% for other fruits. The definitions and sample statistics of demographic variables included in estimating the demand for organic and conventional fruits are presented in Table 2. Because many sample households did not purchase organic fruits, we estimate a censored demand system (see the data and methods section for details). In the first step, a probit model was estimated to predict the likelihood that a household would purchase each fruit category. The prediction results are then incorporated in the second-step demand equations. For brevity, we report the probit results for organic fruits only, focusing on the roles of income and prices in affecting the purchase of organic fruits in discussing our results.

Table 2. Definitions and sample statistics of demographic variables.

Variable	**Definition**	**Non-Buyers**	**Buyers**
Continuous variables			
Household size	Number of members in households	2.33	2.33
		(1.29)	(1.29)
Income	Household income as a % of Federal poverty level	408.42	461.09
		(265.75)	(299.80)
Binary variable (yes = 1; 0 = no)			
Child	Presence of a child(ren)	0.22	0.22
White	Race is white	0.75	0.73
Black	Race is black	0.13	0.13
Hispanic	Race is Hispanic	0.07	0.08
Oriental	Race is Asian	0.04	0.05
Other race	Race is others (ref.)	0.01	0.01
East	Resides in East region of the country	0.22	0.21
Central	Resides in central region	0.18	0.14
South	Resides in South region	0.39	0.35
West	Resides in South region (ref.)	0.21	0.30
Urban	Resides in an urban area	0.86	0.89
Married	Dual-headed household	0.58	0.60
Unemployed (F)	Female household head unemployed	0.37	0.39
≤ High school	Max. education of head is HS or lower (ref.)	0.20	0.14
Some college	Max. education of head is some college	0.31	0.27
≥ College	Max. education of head is college grad. or higher	0.49	0.59
Age < 40	Oldest head age ≤ 40 (reference)	0.09	0.10
Age 40−64	Oldest head age 41–64	0.62	0.60
Age ≥ 65	Oldest head age ≥ 65	0.29	0.30
Sample size		1,676	5,020

Notes: Households that purchased only conventional fruits are categorized as non-buyers. Numbers in parentheses are standard deviations for continuous variables only.

2.1. The Role of Income

The effect of income on the purchase of organic fruits can be traced in three parts. First, income may affect the decision to purchase organic fruits (the participation effect). Second, it is expected that spending on fresh fruits rises with income (the Engel curve effect). Third, as the spending on fresh fruits increases, so does the spending on organic fruits (the expenditure elasticity). The participation effect is investigated by the probit model, as a part of the censored demand system. The censored demand estimation also produces expenditure elasticity estimates. The Engel curve effect is investigated by a separate regression in which spending on fresh fruits is regressed on income and household socio-demographic characteristics.

Household income, education, region, and employment status of a female head are found to have significant effects on the likelihood of purchasing some organic fruits (Table 3). Specifically, households with higher income are more likely to purchase three organic fruits—apples, strawberries, and other fruits. No significant relationship between income and the purchase of organic bananas, grapes, or oranges is found.

Table 3. First-step probit estimates of organic fresh fruit demand.

Variable	Apples	Bananas	Grapes	Oranges	Strawberries	Others
Constant	–1.530***	–1.406***	–2.198***	–2.109***	–2.152***	–1.308***
	(0.187)	(0.185)	(0.321)	(0.289)	(0.269)	(0.170)
Child	0.084	–0.029	–0.036	–0.093	–0.007	0.011
	(0.079)	(0.073)	(0.105)	(0.111)	(0.107)	(0.071)
White	–0.198	0.037	0.244	0.009	0.070	–0.172
	(0.157)	(0.162)	(0.290)	(0.253)	(0.230)	(0.143)
Black	–0.133	0.238	0.384	0.233	0.082	–0.130
	(0.167)	(0.169)	(0.298)	(0.263)	(0.241)	(0.152)
Hispanic	–0.048	0.172	0.462	0.195	0.056	–0.052
	(0.173)	(0.175)	(0.303)	(0.270)	(0.251)	(0.158)
Oriental	–0.136	–0.066	0.458	0.036	0.149	–0.190
	(0.187)	(0.191)	(0.317)	(0.291)	(0.259)	(0.171)
East	–0.135**	–0.183***	–0.064	–0.058	–0.122	–0.211***
	(0.066)	(0.061)	(0.092)	(0.09)	(0.083)	(0.059)
Central	–0.235***	–0.205***	–0.127	–0.191*	–0.185**	–0.282***
	(0.075)	(0.067)	(0.104)	(0.107)	(0.096)	(0.067)
South	–0.181***	–0.203***	–0.049	–0.185**	–0.238***	–0.244***
	(0.059)	(0.054)	(0.081)	(0.084)	(0.076)	(0.052)
Urban	0.099	0.042	0.096	0.026	0.216**	0.111*
	(0.073)	(0.063)	(0.100)	(0.102)	(0.103)	(0.065)

Table 3. Cont.

Variable	Apples	Bananas	Grapes	Oranges	Strawberries	Others
Married	0.093	0.088*	–0.050	–0.036	–0.049	–0.076
	(0.057)	(0.052)	(0.075)	(0.079)	(0.074)	(0.051)
Unemployed (F)	0.110**	0.085**	0.021	0.103	0.115*	0.130***
	(0.048)	(0.044)	(0.066)	(0.069)	(0.063)	(0.044)
Some college	0.165**	0.093	–0.081	–0.092	–0.033	0.148**
	(0.074)	(0.065)	(0.093)	(0.099)	(0.09)	(0.065)
≥ College	0.282***	0.232***	0.041	0.051	0.181**	0.250***
	(0.071)	(0.062)	(0.088)	(0.093)	(0.090)	(0.063)
Income × 10^{-2}	0.019**	0.003	–0.009	0.019	0.040***	0.032***
	(0.009)	(0.008)	(0.013)	(0.012)	(0.010)	(0.008)
Household size	–0.022	–0.008	0.036	0.060	–0.019	0.019
	(0.029)	(0.027)	(0.037)	(0.038)	(0.040)	(0.026)
McFadden's R2	0.019	0.013	0.010	0.015	0.031	0.021
% correct	91.80	88.90	96.80	97.20	96.20	87.90

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

Households with higher educational attainment are more likely to purchase organic apples, bananas, strawberries, and other fruits. Households residing in the Eastern, Central, and Southern regions are all less likely to purchase some organic fruits (oranges, strawberries, and other fruits) than households in the Western region.

The Engel curve relationship between income and total spending on fresh fruits is found to be positive at the 1% significance level (Table 4). Using the mean values for income (424% of the Federal poverty level) and spending ($123 per year), a 1-percent increase in income on average is found to increase the spending on fresh fruits by 0.19 percent. As will be discussed later, a 1-percent increase in the spending on fresh fruits would result in an increase of 0.81 to 1.03 percent in the spending of organic fresh fruits (the expenditure elasticities). Multiplying the expenditure elasticities by the 0.19-percent Engel Curve effect would result in the estimates of the increase in organic fruit spending as the income rises by 1 percent. Household spending on fresh fruits is also found to rise with household size, educational attainment, and age of the household head. Total spending on fresh fruits varies by race (Hispanic and oriental households spend the most, whereas Black households spend the least) and by region (the Western region spends the most).

Table 4. Engel curve: income and spending on organic and conventional fresh fruits.

Variable	Coefficient	SE
Constant	75.31***	7.00
Income	5.57***	0.60
Household Size	16.56***	1.68
Child	–3.97	5.46

Table 4. Cont.

Black	–24.20***	4.60
Hispanic	10.33*	5.87
Oriental	22.53***	13.30
Others	–11.67	11.79
White	reference	
Central	–16.41***	4.91
East	–15.75***	4.57
South	–16.96***	4.08
West	reference	
Age < 40	–66.75***	6.23
Age 40-64	–43.73***	3.54
Age ≥ 65	reference	
Some college	14.72***	4.46
≥ College	35.49***	4.35
≤ High school	reference	
Urban	13.65***	4.48
Rural	reference	
Adj. R-squared	0.080	
Sample size	6696	

Note: Levels of statistical significance: *** = 1%, ** = 5%, and * = 10%.

Demand elasticities computed from the censored demand system are presented in Table 5. Parameter estimates for the censored demand system are not reported; they are available upon request. All expenditure elasticities are positive at the 1% significance 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 fresh fruits, consumers would allocate approximately the same proportional increase to their purchase of conventional and organic fresh fruits.

Table 5. Price and total expenditure elasticities (uncompensated measures).

	Organic Fruits					
Product	**Apples**	**Bananas**	**Grapes**	**Oranges**	**Strawb's**	**Others**
Organic						
Apples	–1.06***	0.65***	–0.55*	0.07	0.05	0.41***
Bananas	1.05***	–3.19***	2.72***	–1.51***	0.10	–0.16
Grapes	–0.65*	1.97***	–3.54***	1.78***	–0.49	–1.13***
Oranges	0.08	–0.98***	1.66***	–0.92	–0.82*	0.11
Strawberries	0.06	0.08	–0.50	–0.90**	–0.36	–0.61***
Other fruits	0.32**	–0.07	–0.75***	0.07	–0.39***	–0.01

Table 5. Cont.

Conventional						
Apples	0.03	–0.05	0.19***	–0.09	0.18***	–0.02
Bananas	–0.16***	0.23***	–0.03	0.14*	0.05	0.02
Grapes	0.02	–0.13***	0.05	0.05	0.04	–0.06
Oranges	–0.19***	–0.03	0.03	0.03	0.18***	–0.02
Strawberries	0.00	–0.05	0.01	–0.15*	–0.02	–0.11***
Other fruits	0.08***	0.00	–0.10***	0.01	–0.14***	0.04*

	Conventional Fruits						Total
Product	**Apples**	**Bananas**	**Grapes**	**Oranges**	**Strawb's**	**Others**	**Expend.**
Organic							
Apples	0.10	–0.46***	0.05	–0.40***	0.00	0.16	0.99***
Bananas	–0.20	1.13***	–0.53***	–0.10	–0.20	0.08	0.81***
Grapes	0.73***	–0.10	0.15	0.08	0.04	0.21	0.97***
Oranges	–0.32	0.48*	0.12	0.07	–0.44	–0.07	1.03***
Strawberries	0.69***	0.19	0.13	0.45***	–0.06	–0.18	0.99***
Other fruits	–0.06	0.04	–0.13	–0.03	–0.22***	0.23**	0.99***
Conventional							
Apples	–0.83***	–0.08**	–0.08***	–0.08***	–0.11***	–0.08***	1.01***
Bananas	–0.08**	–0.70***	–0.10***	–0.07**	–0.07**	–0.21***	0.98***
Grapes	–0.10***	–0.12***	–0.49***	–0.10***	–0.08**	–0.09***	1.01***
Oranges	–0.12***	–0.10**	–0.12***	–0.57***	0.00	–0.10***	1.01***
Strawberries	–0.13***	–0.09**	–0.08**	0.00	–0.50***	0.11***	1.01***
Other fruits	0.06***	–0.02	–0.03	0.00	–0.04**	–0.85***	1.00***

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

In summary, households with higher income are more likely to purchase some organic fruits and spend more on fresh fruits as a whole, as well as on individual organic and conventional fruits. Therefore, our results appear to refute the notion that income does not track spending for organic fresh fruits, a major player in the organic food sector.

2.2. The Role of Price

The own-price demand elasticities are negative at the 1% significance level for three organic fruits (apples, bananas, and grapes) and all six categories of conventional fruits (Table 5). The own-price elasticities for organic oranges and strawberries, as well as other organic fruits are negative, but they are not significant. Among those with significant own-price elasticities, the demand for organic fruits is found to be price elastic, whereas the demand for conventional fruits is price inelastic. Specifically, our estimates of organic own-price elasticities are –1.06 for apples, –3.19 for bananas, and –3.54 for grapes. The results suggest that as prices of these organic fruits decline by 1%, we would expect demand to increase by 1.06% for apples, 3.19% for bananas, and 3.54% for grapes.

The finding of a highly elastic demand for organic fruits is to be expected given that organic produce typically commands a price premium [7] with a small market share. There is no empirical study that reports price elasticities for organic fruits. Glaser and Thompson [9] reported own-price elasticities for four organic frozen vegetables (broccoli, corn, green peas, and green beans) ranging from –1.63 to –2.27.

Our results also suggest that the demand for conventional fruits is price inelastic with elasticities of –0.49 (grapes), –0.50 (strawberry), –0.57 (oranges), –0.70 (bananas), –0.83 (apples), and –0.85 (other fruits). In a recent study on the demand for conventional fresh fruits, Brown and Lee [18] reported similar elasticities of –0.52 for apples, –0.54 for bananas, –0.56 for grapes, and –0.67 for oranges.

There are 66 pairs of cross-price elasticities estimated among the 12 categories of organic and conventional fruits. Half of the cross-price elasticities, or 34 pairs, are statistically significant at the 10% significance level or lower. Positive (negative) cross-price elasticity indicates that the demand for a fruit rises when the price of a different fruit rises (falls), suggesting the two fruits are gross substitutes (complements). Complementary relationships are found more often than a substitution relationship between most organic and conventional fruits. Among the six organic fruits, there are 8 significantly positive and 10 significantly negative cross-price elasticities. In contrast, the results show that almost all conventional fruits are complements to each other; only conventional strawberries have a significant substitution relationship with other conventional fruits. As with the own-price elasticities, all conventional fruits 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 5, among the 10 significant cross-price elasticities between organic and conventional fruits, six are positive and four negative. This result implies that consumers tend to increase their purchases of organic fruits when there is an increase in the price of conventional fruits. On the other hand, there are seven positive and seven negative significant cross-price elasticities between conventional and organic fruits. The results suggest that consumers are more likely to substitute organic fruits for conventional fruits than the other way around. It must be noted that among the significant cross-price elasticities, most organic fruits are substitutes for conventional fruits whereas organic fruits could be either substitutes or complements for conventional fruits. The finding is to be expected given that organic fruits are priced higher than conventional fruits, making it easier to switch from conventional to organic fruits when organic fruits become relatively inexpensive and the prices of conventional fruits increase.

Additionally, the magnitudes of the cross-price elasticities between conventional and organic fruits are larger, in general, than those between organic and conventional fruits, suggesting that changes in the prices of conventional fruits will 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. Glaser and Thompson [9] also observed a similar asymmetry in cross-price responses, although they found only two pairs of significant cross-price elasticities between corn and organic and conventional broccoli. 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.

3. Data and Methods

3.1. Nielsen Homescan Panel—Retail Purchase Data

The Nielsen Homescan panel consists of households that provide food purchase data for at-home consumption and is representative of the United States. Each household is supplied with a scanner device that the panelist uses at home to record grocery items purchased at all retail outlets with the Uniform Product Code (UPC). A subsample of the households called the 'Fresh Foods Panel' is supplied with a code book from Nielsen that allows the panel to record non-UPC items, or random-weight foods, in addition to UPC-coded or packaged fresh foods. This subsample is vital to the analysis of fresh fruits. In 2006, the Fresh Foods Panel included 7,534 households who reported purchases of food products sold with a UPC, such as packaged fresh fruits, and as random weight (i.e., loose fruit) 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 a unit value, which is derived by dividing total expenditure, net of any promotional or sales discounts, by the quantity purchased. The Homescan data also include product characteristics and promotional 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 the estimation of the censored demand system and the Engel Curve effect.

3.2. 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 [19] for *n* fruit products, in expenditure shares (s_i) form:

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

where p_1, ..., p_n are prices, M is total fresh fruit expenditure, and $D = \Sigma_{k=1}^{n} \alpha_k + \Sigma_{k=1}^{n} \Sigma_{j=1}^{n} \beta_{kj} \log(p_j / M)$, which is the sum of the numerator, 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

$$\beta_{ij} = \beta_{ji} \text{ for all } i,j \tag{2}$$

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

$$\alpha_i = \alpha_{i0} + \sum_{\ell=1}^{L} \alpha_{i\ell} h_\ell, \ i = 1,...,n-1. \quad (3)$$

The linear demographic specification was also followed in other studies with the Translog demand system [20] and the linear approximate almost ideal demand system [21]. The parameters to be estimated are $\alpha_{i0}, \alpha_{i\ell}$ and β_{ij}. Such demographic specifications for the n – 1 equations (only) are explained below.

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 [20,22-24], 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 [25], more formally motivated with a multivariate sample selection model [24], provides a practical solution to the problem.

Let $x = [\log(p_1/M),...,\log(p_n/M), h_1,...,h_L]'$ 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 right hand side of the share equation (1), and an unobservable error term e_i. Each equation is subject to the sample selection rule [26],

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

such that each indicator d_i is modeled with a binary probit

$$d_i = 1(z'\gamma_i + u_i > 0), \ i = 1,...,n, \quad (5)$$

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 $\mathcal{N}(0,1)$.

The expenditure shares in equation (4) do not add up to unity unless $d_1 = ... = d_n = 1$, that is, when none of the dependent variables are subject to sample selection. We follow the simple approach suggested in Yen and Lin [24], by estimating the first n – 1 equations with the nth good treated as a residual category [27]. The resulting estimates are not invariant with respect to the equation excluded. Yen and Lin [24] 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 $[u_1,...,u_{n-1}, e_1,...,e_{n-1}]'$ is distributed as $(2n–2)$-dimensioned normal distribution with zero means and a finite covariance matrix with elements $\sigma_{ij} \ (i, j = 1,...,2n-2)$, the sample selection model can be estimated with the ML procedure [23]. 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. 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. A practical alternative is to estimate the system with a two-step procedure, motivated by the unconditional mean of the expenditure shares

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

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 follow from the bivariate normality of the error terms (u_i, e_i) for $i = 1,\dots, n-1$, and suggest a two-step estimation procedure which, as initially suggested in Shonkwiler and Yen [25] 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

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

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 [24] 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 [20, Footnote 9].

4. Conclusions

As the organic industry continues to grow and evolve, it faces many production and marketing challenges, including the consequences of its own success. Economic opportunities and potential profitability may result in production expansion, by inducing new players into production as well as encouraging existing producers to expand their production. Meanwhile, rising concerns about diet, health, and environment as well as the ups and downs of the economy will affect consumers' demand and their willingness to pay for organic foods. A better understanding on the nature of the demand for organic produce together with the supply response is essential to gauge future growth of organic agriculture. The study fills a critical empirical void in the extant literature pertaining to the demand for organic foods. Most previous studies on organic demand 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 the retail level remains relatively small, at 3.3% of the $575 billion US foods market in 2007, excluding food service [1]. 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, income is found to positively affect spending on fresh fruits and on some organic fruits. 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 elasticity 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 to be generally two to three times larger than their conventional counterparts [9].

There is strong statistical evidence of asymmetric cross-price effects between organic and conventional fruits. This asymmetry in cross-price elasticities implies 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.

A few caveats exist. First, due to the small proportion of consuming households, demand was aggregated at 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 estimating demand for a broader group of conventional and organic food products.

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