2007

Consumers' preference 182

Analyzing the Effects of State Dependence and Heterogeneity on Consumers' Organic and Conventional Fresh Produce Choices Using Household Level Scanner Data

Working Paper

Colorado State University
University of California, Davis

Yuko Onozaka[1], David S. Bunch[2], Douglas M. Larson[3]

Presented at the Annual Meeting of the
American Agricultural Economics Association
Portland, OR
July 29-Aug. 1, 2007

[1] Yuko Onozaka (Yuko.Onozaka@colostate.edu), Department of Agricultural and Resource Economics, Colorado State University, Fort Collins CO 80523-1172
[2] David S. Bunch (dsbunch@ucdavis.edu), Graduate School of Management, University of California, Davis, One Shields Avenue Davis, CA 95616-8609
[3] Douglas M. Larson (larson@primal.ucdavis.edu), Department of Agricultural and Resource Economics, University of California, Davis One Shields Avenue Davis, CA 95616-8512

1. Introduction

Purchasing food items is becoming increasingly complex for consumers. There are many different kinds of food items, and even products belonging to the same category are differentiated through brand names, labels, and prices. These products are further differentiated by various types of product information and claims related to health (e.g., reduces cholesterol), nutrition (e.g., high in antioxidants), and production method (e.g., organic). Although product differentiation has been a strategy practiced by firms for many years, it is only recently that a large variety of new differentiated agricultural products has been introduced to the market. Examples of such products include those designated as "organic," "fair trade," "cage free," "no antibiotics," and "hormone free." This trend reflects increased consumer demand for a healthier lifestyle, safer food, and more socially conscious production and trade practices.

Product differentiation is based on the premise that consumers have heterogeneous preferences for product characteristics (and also different ability to pay for them); some consumers care about certain product attributes, to varying degrees, and some do not care at all. Firms marketing products with these particular attributes effectively capture a group of consumers who have preferences for certain characteristics by providing them a slightly different product with those preferred characteristics. Since product differentiation exploits heterogeneous consumer preferences, it is natural that most research done on differentiated agricultural products focuses on how such heterogeneity affects the distribution of people's choices across competing products (for example, Loureiro and Hine, 2002; Pelsmacker et al., 2005; Onozaka et al., 2006).

In the case of fresh produce, there are various quality attributes that are important to consumers. Some quality attributes such as freshness and appearance can be observed at the time of the purchase. Better taste is not observable, but can be experienced when the product is consumed. Perishability may also be experienced if there is a lag between the time of purchase and the time of the actual consumption, and this experience could influence product perceptions and therefore future choice behavior. Credence characteristics, on the other hand, can neither be observed nor experienced, yet perceptions regarding these characteristics can also affect product choice.

Although consumers' heterogeneous preferences and how their preferences affect their valuation of various claims related to quality attributes have been studied extensively (for example, Huang, 1996; Govindasamy and Italia, 1999; Loureiro, McCluskey, and Mittelhammer, 2001; Hearne and Volcan, 2006), what is less well-understood is the role of consumers' *experiences* with a product. Experiences can be an important factor for consumer choice on differentiated agricultural products. For example, consumers may expect organic food, cage-free eggs, and antibiotic-free meat to taste better. However, they can not be sure until they try these products. This is because food is an "experience" good that must be tasted to be fully evaluated. Since these products tend to be sold at higher prices, consumers then need to evaluate whether the experience was worth the price premium. Contingent on such evaluations, a consumer may come back and purchase these differentiated products again, or not return. This process is termed state dependence, and is broadly defined as the causal link between past experience and current choice (Heckman, 1981).

As Heckman (1981) states in his seminal work, consumer behavior such that "individuals who have experienced the event under study in the past are more likely to experience the event in the future than are individuals who have not experienced the event (pp. 114)" is observed in many studies (e.g., labor market participation, incidence of accidents, unemployment). Two potential explanations for this observed behavior are; the experience itself somehow altered the individual's preferences or other factors that affect their choices; or each individual has a different propensity to experience an event. The former indicates that the "past experience has a genuine behavioral effect in the sense that an otherwise identical individual who did not experience the event would behave differently in the future than an individual who experienced the event (Heckman, 1981, pp. 115)." The latter indicates that consumer (or population) heterogeneity in underlying time-invariant consumer characteristics or preferences drive an individual to behave in a certain way. Thus, there may be two different factors that are independently or simultaneously driving the choice of purchasing or not purchasing agricultural differentiated products.

Another important point made by Heckman (1981) is in regard to the identification of these two effects. If consumer heterogeneity is present but not accounted for in the model, the effect of state dependence may be overstated, as the model mistakenly accounts for the consumer heterogeneity as state dependence. This is called *spurious* state dependence. Only when the consumers' heterogeneous preferences are accounted for in the same model can one identify the *true* (or *structural*) state dependence. The same argument applies to *true* and *spurious* consumer heterogeneity (Keane, 1997). In other words, in order to identify both *true* state dependence and *true*

consumer heterogeneity, they need to be modeled simultaneously. Data that allow for such an empirical investigation are individual/household level panel data sets that are sufficiently long and wide (Smith, 2005). Specifically, the data set should include enough households (be "wide enough") to adequately represent heterogeneity in the market; at the same time, the data set should include enough observations per household (be "long enough") to allow between-household differences to be identified and also to detect within-household temporal effects (i.e., state dependence). Data unavailability may be one of the reasons why detailed studies to simultaneously identify these two effects (heterogeneity and state dependence) are relatively rare in differentiated agricultural product markets.

Analyzing state dependence in consumer choice provides insight into the future prospects of the market and marketing strategies that cannot be obtained through analyzing heterogeneity in consumer preferences or characteristics alone. For example, if a positive past experience significantly increases the probability of an individual choosing the product, a price promotion or other strategies, such as in-store samples and coupons, would be a more effective marketing tool to increase sales over time, since the presence of this type of behavior amplifies the effect of the price promotion even after the price has returned to normal.

This paper analyzes the effects of state dependence and consumer heterogeneity simultaneously on consumer choices among differentiated agricultural products, with the expanding organic fresh produce market as the example. In particular, we analyze households' decisions on purchase/non purchase of organic/conventional red leaf lettuce at each shopping occasion over a two-year period. State dependence in this choice

setting is associated with past experience with the product (taste, perishability, and overall value of the product perceived by a consumer) affecting the current decision.

Consumer heterogeneity is defined as exogenous, time-persistent preferences that differ among consumers. For example, if a consumer prefers a product that has less pesticide residues, this preference should persistently affect this individual's choices and a researcher may observe that this individual is more likely to purchase the organic version. Together, these two effects are likely to be important for explaining the expansion of organic product markets. Using the organic market as an example will provide an insight into a path that may be taken by researchers studying other differentiated agricultural products.

A flexible discrete choice model, namely a panel mixed nested logit, is used in the estimation to address violations of the IID error term assumptions in standard multinomial logit (MNL) models. A household level scanner panel data set that contains purchase decisions made by hundreds of households over a two-year period is used for the estimation. To the best of our knowledge, this is the first paper to address the effect of state dependence and consumer heterogeneity in the manner required to identify both effects, in the context of agricultural differentiated products. This is also the first paper to use household level scanner panel data to analyze fresh produce items, and as such, provides an example of scanner data preparation and estimation methods for an analysis of this type of product.

2. Literature

Since the objective of this paper is to analyze the effects of state dependence and consumer heterogeneity using household level scanner panel data, the main foci of this literature review are how data were prepared and how state dependence and consumer heterogeneity were modeled in previous studies.

Scanner data provide researchers detailed information on consumers' actual purchases. Many studies have been done using scanner data to analyze consumers' choices and demand in the agricultural economics and marketing literatures.[4] In the area of agricultural economics, the focus has been on sales of food products at the aggregate level. These studies are motivated by policy interests, and the objectives are usually to estimate demand, obtain various elasticities, and derive welfare measures. For example, Jones (1997) used aggregate scanner panel data to analyze own-price, cross-price, and income elasticities for breakfast cereals, groups of carbohydrate products, and milk. Dhar and Foltz (2005) analyzed the consumer benefit from rBST-free and organic labeled milk, while Kiesel et al. (2005) investigated the effect of a biotechnology label on fluid milk demand, both using aggregate scanner data. Thompson and Glaser (2001), Glaser and Thompson (1998) and Glaser and Thompson (2001) used national aggregated scanner data to analyze price premiums and elasticities of organic products. These studies provide insight into the market as a whole, but did not investigate the household level choices.

On the other hand, marketing studies usually focus on consumers' brand choices for packaged goods. Data typically consist of shopping occasions for households over a

[4] Some studies in the industrial organization literature also utilize scanner data to analyze the degree of market power and firms' strategic behaviors. For example, see Vickner and Davies (2002) and Sexton et al. (2005).

certain time period. Many of the studies consider only purchase occasions (e.g., Erdem, 1996; Murthi and Srinivasan, 1999; Keane, 1997), although some include non-purchase occasions (e.g., Chiang, 1991; Chintagunta, 1993; Bucklin and Gupta, 1992).[5] Bodapati and Gupta (2005) pointed out the potential bias when non-purchase occasions were not included in the model. The geographic area studied is usually limited to one region.[6] The objectives in the marketing literature are to analyze how consumers switch among brands or stay loyal to one, how they respond to various marketing variables, such as promotion and special display, and how household heterogeneity affects brand choices.

Scanner Data Preparation

One of the central issues in using scanner data is how to prepare the data. At the most disaggregated level, one entry of scanner data contains a single product purchased by a single household at a certain store at some point in time. The level of detail in scanner data provides researchers a great deal of freedom in determining how data should be prepared for the analysis. However, it also requires that numerous decisions be made before the data are used. One of the important considerations is the level of aggregation and elimination.[7] The typical dimensions of aggregation and/or elimination are by brand, household, and time. For packaged goods, such as breakfast cereals and yogurt, there may be hundreds of separate UPC[8] codes of relevance, if a researcher considers all the attributes (brands, sizes, flavors, fat contents, and so on); thus, a researcher may choose

[5] A no purchase occasion in household level scanner data is when a household's store visit is observed but no purchase in the *target* product category occurred.
[6] Sioux Falls, South Dakota seems to be a popular choice, due to the similarity of its population composition to the U.S. population.
[7] Capps and Love (2002) discuss the challenges of preparing scanner data for economic studies and provide some tests that one can perform to determine functional forms.
[8] Universal Product Code (UPC) is a widely used barcode in supermarkets in Unites States.

to use only the major brands (e.g., top four brands that hold 80 percent of the market share) . A researcher also needs to determine which households to include and which to eliminate from the analysis. Some households do not buy the targeted product often enough or do not purchase the targeted product at all. Some households drop out in the middle of the study period, and others appear. Another consideration is aggregation over time, such as weekly or bi-weekly for products with relatively low purchase frequencies (e.g., ketchup).

The degree of data aggregation and/or elimination depends largely on the researcher's judgment. Andrews and Currim (2005) call this aggregation/elimination process "data pruning" and provide some simulation results to guide the decisions.

State Dependence and Consumer Heterogeneity

Analyzing the effect of state dependence is one of the major foci of scanner data analysis in the marketing literature. Scanner data are well-suited for this purpose, since they are available for a sufficiently long time period. An effect of state dependence on a current consumption can be either positive or negative. For example, there are both mental and time costs when deciding among many brands, which could lead a consumer to routinely purchase a single brand. If these effects lead to a pattern of purchases that could be characterized as "habit formation," then this type of behavior will result in positive state dependence (also called inertia). On the other hand, if a household seeks variety, state dependence will be negative since brands purchased in the recent past are less likely to be chosen at a current occasion. It is common to have positive state dependence for goods with relatively low prices and high frequency of purchase (Seetharaman et al., 1999).

The most common form of state dependence is modeled using the brand loyalty variable of Guadagni and Little (denoted as G&L hereafter), which is a weighted sum of exponentially decaying past purchase information and the most recent purchase (the G&L state dependence formation is described in more detail when the model is discussed later). The G&L state dependence variable is employed widely, for example, in Ron et al. (1996), Keane (1997), Seetharaman (2003), and Swait and Andrews (2003).[9] Another common specification is a dummy variable for the last brand purchased (LBP). This is a special case of the G&L state dependence variable, which places emphasis on the recent brand choice with no decaying past purchases; example of a study using this variable is Bucklin and Gupta (1992). Other specifications of state dependence are the "wear-off effect," a logarithmic transformation of the number of days since the last purchase (Seetharaman and Chintagunta, 1999), and a purchase share of the brand (Murthi and Srinivasan, 1999). In all these analyses, parameters for state dependence are reported to be positive and significant, and are therefore important to include in purchase models.[10]

Consumer heterogeneity is another main focus of the studies in the marketing literature. In these studies, consumer heterogeneity is most commonly modeled as a random component of preferences which is unobserved by researchers (e.g., Abransom et al., 2000; Keane, 1997; Roy et al., 1996), and generally reported as significant. Other forms of heterogeneity employed in marketing models are demographic variables and purchase histories (e.g., Bucklin and Gupta, 1992).

---

[9] It is considered in the environmental and resource economics literature as well. Recently, Smith (2005) used the G&L state dependence variable to analyze fishermen's location decisions.

[10] A similar but different way of incorporating the past into present choices is to include serially correlated error terms, typically a First Order Autoregressive Process. Many studies included autoregressive error terms into the model, and conclude that it is either insignificant, or very small in magnitude (e.g., Keane, 1997; Abramson, et al., 2000; Seetharaman, et al., 2003; Chib, et al., 2004)

It is important to include both state dependence and consumer heterogeneity in the model, if both are suspected to be present. As Heckman discusses (1981, pp. 114), the effect of unobserved consumer heterogeneity can be mistaken as the causal link between past and present. This is called spurious state dependence. The opposite is also true, that failure to account for state dependence will exaggerate the effect of heterogeneity when state dependence is present (Keane, 1997).

3. Data

The data used for the analysis in this paper were created from original scanner data provided by a Northern California supermarket chain (denoted as Chain X, hereafter). This data set is unique in the sense that it was not obtained through a marketing company, such as AC Nielsen or IRI. Thus, this data set is not subject to the data manipulation/cleaning process routinely done by marketing companies. We have total control over how we prepare the data. However, all the data are from one regional supermarket chain, which limits the ability to generalize the results of this analysis. Still, this unique data set can provide useful insights on the organic market.

Of the produce items that were available, fresh red leaf lettuce was selected for the analysis for several reasons. First, it is one of the highest selling fresh produce items, with both organic and conventional offerings available in this supermarket chain. Second, both types of red leaf lettuce are available throughout the year. Third, it has sufficient price variability.[11] The data cover a period of two years, from 10/29/2002 to 10/31/2004. Shopping trips with and without red leaf lettuce purchases were identified for all

[11] Other popular products, such as bananas, have virtually no price variability. This causes a problem identifying the price coefficient.

individuals in the data.[12] Each observation in the data set represents a shopping occasion, with or without the purchase of red leaf lettuce. In addition, each observation contains a customer ID, an order number that identifies the shopping occasion, the date of the shopping occasion, store code, total expenditure for all goods purchased on the shopping occasion, the UPC code if a red leaf lettuce purchase was made, number of heads purchased, expenditure on the product, name of the product if a purchase was made, and prices of the conventional and organic types for that shopping trip. There are 22,948 shoppers who bought red leaf lettuce at least once during the two-year period. The total sales of conventional and organic red leaf lettuce were $81,615.66 and $15,564.83, respectively. Thus, organic purchases comprised 16% of the total red leaf lettuce dollar sales. The average price for conventional red leaf lettuce was $1.03 per head, while that of organic red leaf lettuce was $1.56 per head. The average organic price premium was $0.53, which was more than 50% of the conventional price.

Considering choices between two types of fresh produce items poses both advantages and difficulties compared to studies analyzing packaged goods. Since there are only two products, it is not necessary to reduce the number of "brands." Stock-up by consumers (i.e., consumers purchasing in bulk at times of price promotions) is not an issue for fresh produce. These are major advantages; however there are some challenges as well. First, unlike packaged products, fresh produce may have seasonal supply fluctuations. Upon investigation of price and sales volume fluctuations, we detected no seasonal movement for either conventional or organic red leaf lettuce; therefore, seasonality was not considered in this study. Second, stock-outs are more likely for fresh

[12] No purchase shopping trips are defined as trips where a shopper purchased at least one fresh produce items but did not purchase red leaf lettuce. This is to eliminate more "supplementary" shopping trips where buying produce items are not the major objective of the trip.

produce items due to supply fluctuations and shorter shelf lives. It is important to detect stock-out dates since it affects the number of alternatives that shoppers face at each shopping trip. We defined stock-out dates as dates where no purchases of the products were made even if the store was open.

Related to the stock-out problem is the availability of the organic alternative. From conversations with store managers of the chain, we identified one store that always carries the organic alternative. There are two stores that carry organic products fairly regularly, but not always. Other stores virtually never carry organic unless there is a store-wide promotion on a certain organic product. The decision of whether to carry organic products is made by store managers. For the store that always carries organic options, we can say that if there were no organic purchases made on a certain day, the product was stocked out. For stores that virtually never carry organics, it is safe to say that the organic alternative was not available. However, for the two stores that carry organic products regularly (but not always), it is not possible to unequivocally identify whether the organic alternative was stocked out or not available. Another complication is that we cannot obtain the organic price information if there are no purchases. Thus, for the purpose of the analysis, we assumed that if there were no organic purchase on a certain day for these two stores, the organic option was not available. Among the three stores that carry organic versions regularly or always, there were no problems with stock outs for conventional red leaf lettuce (i.e., no dates were identified with zero purchase volume for conventional red leaf lettuce), while three stock-out dates were identified for organic red leaf lettuce in the store always carrying organic. On these days, shoppers are assumed not to have the option to purchase the organic version.

As in other marketing studies, we need to define the market by identifying "participants" who are potential buyers in the product category (i.e., who consider buying some type of the product) and those who did not stop coming to Chain X during the two-year period of the complete analysis. The selection criteria applied are to include those who made at least four purchases of either conventional or organic red leaf lettuce over the two-year period and came to any of the stores of this grocery chain at least once in each quarter for all eight quarters. This reduces the number of households to 2,748. The number is further reduced by selecting those who mainly (at least 85% of the total shopping occasions) shop at a store that always carries organic red leaf lettuce. For these 768 households, purchases made at two other stores where organic selections are regularly available are included, which makes the number of choice occasions 84,317.

4. Model

State Dependence Variable Formation

We considered the most widely used form of state dependence in the marketing literature introduced by Guadagni and Little (1983). Guadagni and Little's (G&L) state dependence variable for individual i for an alternative j at time t, denoted as X_{ijt}^{GL}, is defined such that

$$(1) \qquad X_{ijt}^{GL} = \alpha X_{ij,t-1}^{GL} + (1-\alpha) D_{ij,t-1}$$

where $D_{ij,t-1}$ takes on the value of 1 if an individual i chooses alternative j at choice occasion t-1, and 0 otherwise. In order to demonstrate how past experiences are

integrated into the current choice, consider t = 3. The G&L state dependence is expressed as

$$(2) \qquad X_{ij3}^{GL} = \alpha X_{ij2}^{GL} + (1-\alpha)D_{ij2}\,.$$

However, X_{ij2}^{GL} is the state dependence variable one time period before (t = 2), thus, by substituting in the state dependence variable at $t = 2$ in equation (2) yields

$$(3) \qquad X_{ij3}^{GL} = \alpha[\alpha X_{ij1}^{GL} + (1-\alpha)D_{ij1}] + (1-\alpha)D_{ij2}$$

Here, one can see the recursive nature of this variable and how the effect of past choices can be incorporated into the current time period. In general, the state dependence variable at time period t can be written as

$$(4) \qquad X_{ijt}^{GL} = \alpha^{t-1}X_{ij1}^{GL} + (1-\alpha)\sum_{k=2}^{t}\alpha^{t-k}D_{ijk-1}\,,\ t = 2,\ldots,T_i$$

As a special case, consider when α = 0 in equation (1). Then G&L state dependence becomes a dummy variable for the last brand purchased (LBP), another popular state dependence variable in the marketing literature.[13] Thus, when the value of α is close to zero, it indicates that the most recent purchases have more influence on the current choice.

[13] This specification of LBP is a brand specific purchase/no purchase dummy variable, created for all the brands considered in the model.

At the other extreme, as α approaches 1, the second term of the equation (1) will drop out, and only the first term that calculates the decaying sum of the past purchases is left. The value of α determines the weight given to the immediate past and the entire history in affecting the current choice.

Note that at the beginning of the time period ($t = 1$), the state dependence variable takes an initial condition. There is no universally accepted way to set the initial condition for the state dependence variable (Keane, 1997). In this paper, we first employed a method described in Keane (1997) and used the first six months of the data as a "burn-in" period to calculate the state dependence variable. In other words, $\widetilde{X}_{ij0}^{SD}$ is set to zero at the beginning of the data set, and state dependence variables are calculated for each time period for six months. Values of the state dependence variables at the end of the six-month period are used as initial conditions X_{ij0}^{SD} for the estimation of the rest of 18 months period. However, we discovered that the majority of the people in the dataset had initial conditions very close to zero, perhaps due to the low purchase incidences in the data set. Rather than losing 6 months of data, we decided to set all the initial conditions to be zero.[14]

As discussed in Smith (2005), the inclusion of the state dependence variable introduces complications for the estimation. This is because the parameters are no longer linear as the utility function includes the product of α and the coefficient for state dependence (denoted as β_{SD}). In addition, the state dependence variable at any given time depends on all past choices. Thus, the state dependence variable X_{ij0}^{SD} needs to be

[14] We estimated selected models with 18 months of data (6 months burn-in period), but the results did not alter qualitatively.

calculated for a given value of α, then multiplied by the state dependence coefficient. This process slows down the computation tremendously. This is especially true for a logit model with random parameters (e.g., mixed logit, panel mixed logit, panel mixed nested logit) as estimating random parameters involves simulations that are computationally intensive. In the marketing literature, it is common to pre-set the value of α, typically to 0.8 based on past research, for packaged products (for example, Gupta, 1988; Chiang, 1991; Chintagunta, 1993; Roy et al., 1996). There are few papers that estimate both α and β_{SD} (for example, Keane, 1997; Seetharaman, 2003 in marketing; Smith, 2005 in environmental economics). In this paper, with a large number of observations and multiple random parameters, it is major computational burden to estimate both α and β_{SD}. Instead, we performed a grid search. We estimated the most general model with $\alpha = 0.1, 0.5, 0.7, 0.8, 0.85, 0.9, 0.95, 0.99$, and compared the values of the likelihood function. The value $\alpha = 0.9$ provided the highest likelihood; thus, we used this value for the following model estimations. The value $\alpha = 0.9$ indicates slightly larger weights on the entire purchase history than on the most immediate past, compared to typical packaged products with $\alpha = 0.8$.

Choice Model Specification

We estimated a model using all 768 "participants" as defined above. At each choice occasion, a consumer has three choices: purchase the conventional product, purchase the

organic product, or do not make a red leaf lettuce purchase.[15] The indirect utility function associated with each alternative at each choice occasion is

$$(5) \qquad \widetilde{U}_{ijt} = \widetilde{V}_{ijt} + \widetilde{\varepsilon}_{ijt}, \quad \text{for } i = 1,\ldots,I, j = 1,2,3 \text{ and } t = 1,\ldots,T_i$$

where $\widetilde{U}_{ijt}$ is the indirect utility of an individual i for an alternative j at a choice occasion t, $\widetilde{V}_{ijt}$ and $\widetilde{\varepsilon}_{ijt}$ are the deterministic and random components of the indirect utility, respectively, and T_i is the number of choice occasions for an individual i. The deterministic component of the indirect utility function $\widetilde{V}_{ijt}$ is specified as

$$(6) \qquad \widetilde{V}_{ijt} = \alpha_{BUY} + \alpha_{ORG} + \beta_P \ln(P_{ijt} / E_{it}) + \beta_{SD1} X_{it}^{CONV} + \beta_{SD2} X_{it}^{ORG},$$

where α_{BUY} and α_{ORG} are alternative specific constants (ASCs), β_p is a price coefficient, P_{ijt} is the price of the jth alternative that an ith individual faces at shopping occasion t, E_{it} is the total shopping trip expenditure of the ith individual at shopping occasion t, β_{SD1} and β_{SD2} are state dependence parameters, $\mathbf{X}_{it}^{CONV}$ and $\mathbf{X}_{it}^{ORG}$ are state dependence variables for conventional and organic alternatives (as specified in the previous section), respectively. The indirect utility for the "no purchase" option is normalized such that $\widetilde{U}_{i3t} = \widetilde{\varepsilon}_{i3t}$, without loss of generality. If the error term $\widetilde{\varepsilon}_{ijt}$ is assumed to have an IID Type I Extreme Value distribution, the resulting choice model is a multinomial logit

[15] Except for stock-out dates where shoppers only face two alternatives: to purchase conventional red leaf lettuce or no red leaf lettuce purchase.

(MNL). However, in this particular choice setting, the MNL specification of the error term may not be reasonable. First, in panel data, individuals are making repeated choices. It is likely that choices made by the same individual are correlated, due to the individual's specific preferences that persist over time. When an individual's taste is unobserved and therefore included in the error term, the error terms are intertemporally correlated.[16] This violates the IID assumption of MNL. A related issue is that individual tastes are also likely to be different across people (i.e., taste heterogeneity). If taste heterogeneity is unobserved, this will also lead to a violation of the IID assumption of MNL. Second, the error term assumption of MNL leads to a specific substitution pattern known as Independence of Irrelevant Alternatives (IIA). Under IIA, if one of the alternatives is removed from the choice set, the ratio of choice probabilities among remaining alternatives will stay constant. Consider a situation where a consumer needs to purchase lettuce (e.g., she wants to make salad tonight), and suppose that we remove the "no purchase" option from the choice set. The relative odds between purchasing organic and conventional lettuce is likely to stay the same, so the IIA assumption does not seem to be too limiting. However, if one of the purchase options (either organic or conventional) is removed from the choice set, (e.g., one of the products was out of stock and not available at the time), then the relative odds between purchasing the available product versus not purchasing would be expected to increase, hence, IIA would not hold. Note that the IIA property of MNL can be derived directly from the IID Type I Extreme Value assumption of the error term. Thus, a violation of IIA can also be interpreted as being due to a violation of the IID error term assumption.

[16] If all the taste variations or intertemporal correlations are accounted for in the deterministic portion of the indirect utility function, the IID assumption will hold. However, such situation may be difficult to obtain (Train, 2003).

An individual's taste variation (relative to other individuals) and persistence (within choices by the same individual) can be accounted for by employing the panel mixed logit (PML) model. For the PML model, the indirect utility function in equation (5) is rewritten as

$$(7) \qquad U_{ijt} = V_{ijt} + \varepsilon_{ijt}$$

where V_{ijt} is the deterministic, and ε_{ijt} is the random component of the indirect utility. The deterministic portion, V_{ijt}, is specified as

$$(8) \qquad V_{ijt} = \alpha_{BUY,i} + \alpha_{ORG,i} + \beta_{P,i} \ln(P_{ijt} / E_{it}) + \beta_{SD1} X_{it}^{CONV} + \beta_{SD2} X_{it}^{ORG}.$$

In equation (8), $\alpha_{BUY,i}$ and $\alpha_{ORG,i}$ are individual-specific, alternative-specific constants (ASCs) and $\beta_{p,i}$ is an individual-specific price coefficient. The presence of a subscript i but no subscript t on ASCs and the price coefficient reflects the fact that the tastes vary among individuals (consumer heterogeneity), but they persist over time for the same individual.[17] These individual-specific values are assumed to be drawn from a population distribution for each parameter. These parameters are called random coefficients (Train, 2003). In this case, ASCs are assumed to be distributed normally so they can affect preferences in a positive or negative way. The price coefficient, on the other hand, is

[17] If $\alpha_i = \alpha \ \forall i$, i=1,…,I, then it is a fixed parameter.

assumed to have a log-normal distribution in order to restrict the sign of the coefficient to be negative.[18] The distributional assumptions for the random coefficients are therefore

(9) $\alpha_{BUY,i} \sim N(\overline{\alpha}_{BUY}, \sigma^2_{BUY})$,

(10) $\alpha_{ORG,i} \sim N(\overline{\alpha}_{ORG}, \sigma^2_{ORG})$,

(11) $\beta_{P,i} \sim \text{log normal}(c, s)$,

where $\overline{\alpha}$'s are means and σ's are standard deviations of the normal distributions, and distributional parameters c and s represent the central tendency and spread for the log-normal distribution.

One specific type of violation of the IIA assumption can be accounted for by employing a nested logit (NL) model. The NL model assumes the error has a specific type of Generalized Extreme Value (GEV) distribution, instead of Type I Extreme Value. One way to illustrate the NL model is to use the nesting structure described in Figure 1. A consumer first decides whether she will purchase or not. If a purchase is made, there is a choice between conventional and organic. In this setting, choices can be correlated within a nest, thus, allowing substitution patterns such as the one described above.[19] The general form of the choice probability of an individual i choosing an alternative j that belongs to the nest k among K nests at a choice occasion t in the NL model is given by

[18] This restricts the price coefficient to be negative. More importantly, this restricts the marginal utility of money, which is the negative of the price coefficient in this case, to be positive.

[19] The description of a sequential choice process is useful for narrative purposes, but the choice can also be interpreted as a single choice where the unobserved disturbances for the purchase options are positively correlated.

$$(12) \qquad L_{ijt} = \frac{e^{\tilde{V}_{ijt}/\lambda_k}\left(\sum_{j\in \mathbf{B}_k} e^{\tilde{V}_{ijt}/\lambda_k}\right)^{\lambda_k - 1}}{\sum_{l=1}^{K}\left(\sum_{j\in \mathbf{B}_k} e^{\tilde{V}_{ijt}/\lambda_l}\right)^{\lambda_l}}.$$

where V_{ijt} is the deterministic component of the indirect utility function specified in equation (6). The parameter λ_k in equation (12) is called the inclusive value parameter. It parameterizes the degree of correlation among purchase options. When λ_k is equal to 1, it means that the choices in the kth nest are not correlated and IIA holds. If all the λ's are equal to 1, then the NL model collapses to the MNL model.[20] For purchase options (j = 1,2), the choice probability is

$$(13) \qquad L_{ijt} = \frac{e^{\tilde{V}_{ijt}/\lambda}\left(e^{\tilde{V}_{i1t}/\lambda} + e^{\tilde{V}_{i2t}/\lambda}\right)^{\lambda-1}}{e^{\tilde{V}_{i3t}} + \left(e^{\tilde{V}_{i1t}/\lambda} + e^{\tilde{V}_{i2t}/\lambda}\right)^{\lambda}} \qquad \text{for } i = 1,\ldots,I,\ j = 1,2, \text{ and } t = 1,\ldots,T_i$$

For the no purchase option (j = 3), λ is 1, since there is only one alternative in this nest. The choice probability is thus

$$(14) \qquad L_{i3t} = \frac{e^{\tilde{V}_{i3t}}}{e^{\tilde{V}_{i3t}} + \left(e^{\tilde{V}_{i1t}/\lambda} + e^{\tilde{V}_{i2t}/\lambda}\right)^{\lambda}} \text{ for } i = 1,\ldots,I,\ j = 1,2, \text{ and } t = 1,\ldots,T_i.$$

[20] Testing whether λ_k =1 for all the nests can be used to test this specification.

By substituting V_{ijt} with $\widetilde{V}_{ijt}$, specified in equation (8), in equations (12) to (14) yields the panel mixed nested logit (PMNL). The likelihood function for an individual i to have a sequence of choices $s = (s_1, s_2, \ldots, s_{Ti})$ in PMNL is expressed as

$$(15) \qquad L_i = \int_{\beta} \prod_{t=1}^{T_i} \frac{e^{V_{is_t t}/\lambda_k} \left(\sum_{j \in \mathbf{B}_k} e^{V_{ijt}/\lambda_k}\right)^{\lambda_k - 1}}{\sum_{l=1}^{K} \left(\sum_{j \in \mathbf{B}_k} e^{V_{ijt}/\lambda_l}\right)^{\lambda_l}} f(\hat{\mathbf{a}}) d\hat{\mathbf{a}}$$

where the nested logit kernel is conditional on the parameter vector $\grave{\mathbf{e}} = (\overline{\alpha}_{BUY}, \overline{\alpha}_{ORG}, \sigma^2_{BUY}, \sigma^2_{ORG}, c, s)$, and $f(\beta)$ is the joint density function of the estimated parameters (Train, 2003). In the PMNL model, the NL inclusive value parameter λ accounts for within-nest correlation while random parameters in the PML account for the within-individual correlation and across-individual heterogeneity. The expression in (15) does not have a closed form solution. However, simulated maximum likelihood estimation can be employed to estimate the model (Train, 2003). Train's simulated maximum likelihood estimation routine in GAUSS (Train et al., 1999) is used for the estimation. However, the code only estimates the panel mixed logit, not the PMNL. For this reason, the likelihood function in Train's GAUSS code is modified to have the form of equation (15) for the estimation of a PMNL.[21]

Taste Variation in State Dependence

[21] We also tried BIOGEME (Bierlaire, 2003; Bierlaire, 2005), which obtained about the same results for selected specifications.

Another thing to consider is the possibility that state dependence also varies across people. State dependence captures the effect of past experience on the current choice, and it is reasonable to assume that past experience might affect people differently. For example, one person may formulate a habit and purchase the same brand over and over again, while another might demonstrate variety seeking behavior. The former implies positive state dependence, while the latter implies negative state dependence. Both are valid market behaviors. In order to account for this possibility, we also include a model where β_{SD1} and β_{SD2} vary across individuals. The normal distribution is appropriate for the specification of random state dependence parameters since both positive and negative values are valid. The distributional assumptions for random state dependence parameters are;

$$(16) \quad \beta_{SDj,i} \sim N(\overline{\beta}_{SDj}, \sigma^2_{SDj}), j = 1,2,$$

where $\overline{\beta}_{SDj}$'s and σ_{SDj} 's are mean and standard deviation parameters, respectively. With the random state dependence parameters, the indirect utility function is specified as

$$(17) \quad \overline{V}_{ijt} = \alpha_{BUY,i} + \alpha_{ORG,i} + \beta_{P,i} \ln(P_{ijt} / E_{it}) + \beta_{SD1,i} X^{CONV}_{it} + \beta_{SD2,i} X^{ORG}_{it}.$$

The parameter vector in equation (15) now includes the state dependence parameters,

$$(18) \quad \grave{e} = (\overline{\alpha}_{BUY}, \overline{\alpha}_{ORG}, c, s, \overline{\beta}_{SD1}, \overline{\beta}_{SD2}, \sigma_{SD1}, \sigma_{SD2}).$$

5. Estimation Results

The estimation results are presented in Table 1. Model 1 is the benchmark case, including neither state dependence nor consumer heterogeneity. Model 2 only includes consumer heterogeneity, but not state dependence. Model 3 includes state dependence but does not include consumer heterogeneity. Model 4 includes both consumer heterogeneity and state dependence. Model 5 includes random parameter state dependence.[22] The PMNL model in equation (15) is estimated when consumer heterogeneity is accounted for (models 2, 4, and 5), and the NL model in equation (12) is estimated when consumer heterogeneity is ignored (models 1 and 4).

The results of likelihood ratio tests indicate that including either consumer heterogeneity or state dependence alone would improve the model fit compared to a benchmark case (restrict models 2 and 3 to model 1).[23] Adding state dependence variables to the consumer heterogeneity model (model 2 to model 4) significantly improves the model fit by likelihood ratio tests. The most notable change from model 2 to model 4 is the change in price coefficients. Although the central tendency (c) remains virtually unchanged, the spread parameter (s) is smaller when state dependence is accounted for. The size of the standard deviation for the "buy" constant (σ_{BUY}) is also smaller and less significant in model 4 compared to model 2. These results indicate that

[22] A model in which all the parameters are specified as random parameters did not converge; thus, the price coefficient is estimated as fixed. It is pointed out by Revelt and Train (1998) and Hensher, et al. (2005) that when all the parameters are random coefficients, the model may not be identified. Thus, we set the price coefficient to be fixed to estimate a model where state dependence parameters are random parameters.

[23] The model fit can be further compared using the values of adjusted ρ which is calculated as 1-((LL(EST)-No.Param)/LL(NULL)). The (unadjusted) ρ is also called pseudo R^2, and it is a measure of goodness of fit for discrete choice models (Train, pp. 72). The adjusted ρ penalizes the added parameters, analogous to adjusted R^2.

the population heterogeneity is overstated for preference for purchases when state dependence is not included in the model. The standard deviation for the organic constant (σ_{BUY}) is virtually unchanged. The facts that the organic constant is stable and the standard deviations for both ACSs and the spread parameter for the price coefficient are highly significant indicate the presence of *true* consumer heterogeneity. The inclusive value parameter is significantly smaller in model 2 than in model 4, implying larger correlation among purchase choices in model 2. Thus, not only consumer heterogeneity, but also the correlation among the purchase alternatives, is exaggerated in the consumer heterogeneity only model.

Adding consumer heterogeneity to the state dependence only model (going from model 3 to 4), significantly decreases the magnitude of the state dependence parameters. This demonstrates that ignoring consumer heterogeneity overstates the effect of state dependence. It is also interesting that both state dependence parameters turned out to be about the same size after accounting for consumer heterogeneity, while the organic state dependence variable was significantly larger before consumer heterogeneity was accounted for. This shows that part of the organic state dependence captured in this model was really consumer heterogeneity. The inclusive value parameter is larger in model 3, indicating that the purchase alternative correlation is actually *smaller* in the state dependence only model.

Interestingly, the magnitude of the inclusive value parameter is sensitive to the model specification. The magnitude decreased (which implies larger correlation among purchase alternatives) when only consumer heterogeneity was included, while it increased (which implies smaller correlation) when only state dependence was included.

When both are accounted for, the inclusive value parameter took a value that falls between the consumer heterogeneity only and state dependence only models. It makes sense that the estimates of the inclusive value parameter might change in the absence of consumer heterogeneity or state dependence because the inclusive value parameter could be used to compensate for the missing information.

Model 5 explores consumer heterogeneity in state dependence by treating the state dependence parameters as random parameters. The likelihood ratio test is significant compared to model 4, indicating its superior explanatory power. The means of the state dependence parameters are virtually unchanged compared to model 4, although the organic state dependence parameter became slightly smaller. The magnitude of the standard deviation of the conventional state dependence (σ_{SD1}) is about one-tenth of that of organic state dependence (σ_{SD2}). The t-ratio for σ_{SD1} is 0.402, not significant even at the ten percent level of significance. On the other hand, σ_{SD2} has a t-ratio of 5.008, significant at the one percent level. These results indicate that even though the sizes of the means of state dependence parameters are similar for both types of products, the conventional state dependence is homogeneous among consumers, while the organic state dependence is heterogeneous. However, the size of the mean and standard deviation parameters for the organic state dependence shows that virtually all the consumers have positive state dependence.[24]

6. Discussion

[24] The 95% confidence interval is (2.17, 2.73)

The estimation results for model 5 (the preferred model) show evidence of spurious relationships when only state dependence or consumer heterogeneity is accounted for individually, and that models simultaneously accounting for both are superior. The results also show the presence of both *true* consumer heterogeneity and *true* state dependence in consumers' choices of conventional and organic fresh produce, because neither effect goes away when both effects are estimated simultaneously. Several other observations can be made. First, state dependence is significantly positive for both organic and conventional choices, indicating that consumers are more likely to choose the same "type" of produce, either organic or conventional, once they have experienced it. This result is more important for organic choices, because it is reasonable to assume that everybody has experienced the conventional red leaf lettuce before, and an organic experience would be more "new" to them. This finding may suggest some insight for the future expansion of the organic market; the organic market may have a potential to expand even further if consumers can be persuaded to try organic products. Second, positive state dependence could also suggest the presence of a psychological barrier (either inertia or distrust of unknown products). However, the barrier can be broken more easily once the product is experienced. This might be good news for producers and growers who wish to introduce their differentiated products into the market. Letting people experience the product would help to gain customers with positive state dependence. This is why price promotion could be effective to encourage such a switch.

Third, the size of the state dependence parameters turned out to be about the same for both conventional and organic choices, showing that there is not much difference in terms of the effect of the past choices, organic or conventional. However, the organic

state dependence has significant consumer heterogeneity while the conventional state dependence is homogeneous among consumers. At the same time, the organic state dependence distribution is tight, and virtually all of the population falls on the positive side. This shows that there are indeed some differences among people in how the organic state dependence affects their choices, but the differences are fairly small and, for the most part, all have positive state dependence.

Fourth, the standard deviation of the organic constant is larger than that of the buy constant, indicating more preference heterogeneity for organic purchases. The last observation is that the inclusive value parameters are highly significant, showing that IIA assumption was in fact violated and purchase choices are significantly correlated.

7. Conclusion

This paper examined the effects of state dependence and consumer heterogeneity on consumers' choices of conventional and organic produce using household level supermarket scanner data. We found significant effects of both true state dependence and true consumer heterogeneity, which can only be achieved by accounting for both effects simultaneously. The positive state dependence suggests a barrier for consumers to choose a different "type" of product. However, it also indicates that once they experienced the different type of product, the experience may work as a motivation to lower the barrier. The analysis revealed that consumers are fairly homogenous in how past purchases affect their future decisions for conventional purchases. However, the evidence points out the existence of heterogeneous organic state dependence, although the preference distribution is tight and virtually everybody has positive state dependence.

This result may be more important for organic products, since it is likely that nearly everybody has tried the conventional type before. The presence of the true consumer heterogeneity confirms that consumers' heterogeneous tastes also affect their organic purchase decisions. These results suggest some of the forces for the organic market expansion in the past and potential future expansion. The marketing implication of this research is that price promotion or other marketing strategy to encourage consumers to try the product may be more effective for organic products. For example, a temporary price cut will induce some consumers to switch. The presence of positive state dependence suggests that the "switch" will also make them more prone to choose organic in the future.

The research provides some insights on the dynamic consumer choices of one differentiated product. However, more research is needed using other products to fully understand the complex process of dynamic choices. Accounting for consumer heterogeneity in a more structural way is also important to better explain these choices. Scanner data provides very limited individual information. Augmenting scanner data with survey data, for example, may be necessary.

Reference:

Abramson, C, R. L. Andrews, I.S. Currim, and M. Jones. 2000. "Parameter Bias from Unobserved Effects in the Multinomial Logit Model of Consumer Choice," *Journal of Marketing Research*, Vol. 37, No. 4, pp. 410-426.

Andrews, Rich L. and I.S. Currim. 2005. "An Experimental Investigation of Scanner Data Preperation Stragegies for Consumer Choice Models," *International Journal of Research in Marketing*, 22, pp. 319-331.

Bierlaire, M. 2003. "BIOGEME: A Free package for the Estimation of Discrete Choice Models," *Proceedings of the 3rd Swiss Transportation Research Conference*, Ascona, Switzerland.
http://www.strc.ch/Paper/bierlaire.pdf

Bierlaire, M. 2005. "An Introduction to BIOGEME (Version 1.4)"
http://transp-or2.epfl.ch/biogeme/doc/tutorial.pdf

Bucklin, R.E. and S. Gupta. 1992. "Brand Choice, Purchase Incidence, and Segmentation: An Integrated Modeling Approach," *Journal of Marketing Research*, Vol.29, No.2, pp. 201-215.

Bunch, D.S. 2007. "Theory-Based Functional Forms for Analysis of Disaggregated Scanner Panel Data," working paper?

Bodapati, A.V. and S. Gupta. 2005. "Purchase-Frequency Bias in Random-Coefficients Brand-Choice Models," *Journal of Business & Economic Statistics*, Vol. 23, No. 4.

Capps Jr, O. and A.H. Love. 2002. "Econometric Considerations in the Use of Electronic Scanner Data to Conduct Consumer Demand Analysis," *American Journal of Agricultural Economics,* Vol. 84, No.3, pp. 807–816.

Chiang, J. 1991. "A Simultaneous Approach to the Whether, What and How Much to Buy Question" *Marketing Science*, Vol. 10, No. 4, pp. 297-315.

Chib, S., P.B. Seetharaman and A. Strijenv. 2004. "Model of Brand Choice with a No-Purchase Option Calibrated to Scanner-Panel Data," *Journal of Marketing Research*, Vol. XLI, pp. 184-196.

Chintagunta, P. 1993. "Investigating Purchase Incidence, Brand Choice and Purchase Quantity Decisions of Households" *Marketing Science*, Vol. 12, No. 2, pp. 184-208.

Dhar, T. and J.D. Foltz. 2005. "Milk by Any Other Name...Consumer Benefit from Labeled Milk" *American Journal of Agricultural Economics*, Vol. 87, No. 1, pp.214-228.

Erdem, T. 1996. "Dynamic Analysis of Market Structure" *Marketing Science*, Vol. 15, No. 4, pp. 359-378.

Gaudagni, P.M. and J.D. Little. 1983. "A Logit Model of Brand Choice Calibrated on Scanner Data," *Marketing Science*, Vol.2, No.3, pp. 203-238.

Glaser, L.K. and G.D. Thompson. 1998. "Demand for Organic and Conventional Frozen Vegetables." Paper presented at the American Agricultural Economics Association Annual Meetings, Nashville, TX, 8-11, August.

Glaser, L.K. and G.D. Thompson. 2000. "Demand for Organic and Conventional Beverage Milk." Paper presented at the Western Agricultural Economics Association Annual Meetings, Vancouver, BC, June 29-July 1.

Govindasamy, R. and J. Italia. 1999. "Predicting Willingness-to-Pay a Premium for Organicaly Grown Fresh Produce" *Journal of Food Distribution Research*: 44-53.

Gupta, S. 1988. "Impact of Sales Promotions on When, What, and How Much to Buy," *Journal of Marketing Research*, Vol. 25, No. 4, pp. 342-355.

Hearne, R.R. and M.M. Volcan. 2006. "The Use of Choice Experiments to Analyze Consumer Preferences for Ecolabeled and Organic Produce in Costa Rica." *The Quarterly Journal of International Agriculture*: in press.

Heckman, J.J. 1981. "Statistical Models for Discrete Panel Data" in C.F. Manski, D. McFadden (Eds.), *Structural Analysis of Discrete Data with Econometric Applications*, MIT Press, Cambridge, MA.

Hensher, D, N. Shore, and K. Train. 2005. "Household Willingness to Pay for Water Service Attributes," *Environmental and Resource Economics*, Vol. 32, No. 4, pp. 509-531.

Huang, C.L. 1996. "Consumer Preference and Attitude Towards Organically Grown Produce." *European Review of Agricultural Economics*, 23: 331-342.

Jones, E. 1997. "An Analysis of Consumer Food Shopping Behavior Using Supermarket Scanner Data: Differences by Income and Location" *American Journal of Agricultural Economics*, Vol. 79, No. 5, pp. 1437-1443.

Kiesel, K., D. Buschena, and V. Smith. 2005. "Do Voluntary Biotechnology Labels Matter to the Consumer? Evidence from the Fluid Milk Market" *American Journal of Agricultural Economics*, Vol. 87, No. 2, pp. 378-392.

Keane, M.P. 1997. "Modeling Heterogeneity and State Dependence in Consumer Choice Behavior," *Journal of Business & Economic Statistics*, Vol. 15, No. 3, pp. 310-327.

Loureiro, M., and S. Hine. 2002. "Discovering Niche Market: A Comparison of Consumer Willingness to Pay for Local (Colorado Grown), Organic, and GMO-Free Products" *Journal of Agricultural and Applied Economics*, 34(3): 477-487.
Loureiro, M., J. McCluskey, R. Mittelhammer. 2002. "Will Consumers Pay a Premium for Eco-labeled Apples?" *Journal of Consumer Affairs*, 36(2): 203-19.
Money Magazine. 2006. "Most Educated"
http://money.cnn.com/magazines/moneymag/bplive/2006/top25s/educated.html

Murthi, B.P.S. and N. Srinivasan. 1999. "Consumers' Extent of Evaluation in Brand Choice" *The Journal of Business*, Vol. 72, No. 2. pp. 229-259.

Onozaka, Y., D.S. Bunch, and D.M. Larson. 2005. "Choosing Fresh Produce-What's Important to You? Summary Report" University of California, Davis.
http://www.agecon.ucdavis.edu/aredepart/facultydocs/Larson/summary-report-100505.pdf

Onozaka, Y., D.S. Bunch, and D.M. Larson. 2006. "Consumer Valuation of Organic Related Properties in Fresh Produce Choices:What Are Consumers Paying For?" Working Paper, Department of Agricultural and Resource Economics, University of California, Davis.

Pelsmacker P.D., L. Driesen, and G. Rayp. 2005. "Do Consumers Care about Ethics? Willingness to Pay for Fair-Trade Coffee," *Journal of Consumer Affairs* Vol. 39, No. 2, pp. 363–385.

Revelt, D. and K. Train. 1998. "Mixed MNL Models for Discrete Response," *Journal of Applied Econometrics*, Vol. 15, No. 4, pp. 447-470.

Roy, R., P.K. Chintagunta. and S. Halder. 1996. "A Framework for Investigating Habits, 'The Hand of the Post,' and Heterogeneity in Dynamic Brand Choice," *Marketing Science*, Vol. 15, No. 3, pp.280-299.

Seetharaman, A. 2003. "Probabilistic Versus Random-Utility Models of State Dependence: An Empirical Comparison," *International Journal of Research in Marketing* 20, pp. 87-96.

Seetharaman, A., and P. Chintagunta. 1999. "Investigating Household State Dependence Effects across Categories," *Journal of Marketing Research*, Vol. 36 No. 4. pp. 488-500.

Sexton, R.J., M. Zhiang, and J. Chalfant. 2005. "Grocery Retailer Behavior in Perishable Fresh Produce Procurement," *Journal of Agricultural and Food Industrial Organization*, Vol. 3, Issue 1. http://www.bepress.com/jafio//vol3/iss1/

Smith, M.D. 2005. "State Dependence and Heterogeneity in Fishing Location Choice," *Journal of Environmental Economics and Management*, 50, pp. 319-340.

Thompson, G.D. and L.K. Glaser. 2001. "National Demand for Organic and Conventional Baby Food." Paper presented at the Western Agricultural Economics Association Annual Meetings, Logan, UT, 9-11, July.

Train, K., Revelt, David and Ruud, Paul. 1999. "Mixed Logit Estimation Routine for Panel Data." http://elsa.berkeley.edu/Software/abstracts/train0296.html

Swait, J. and R.L. Andrews. "Enriching Scanner Panel Models with Choice Experiments" *Marketing Science*, Vol. 22, No. 4, pp. 442-460.

Vickner, S.S. and S.P. Davies. 2002. "Estimating Strategic Price Response Using Cointegration Analysis: The Case of the Domestic Black and Herbal Tea Industries," *Agribusiness*, Vol. 18, No. 2, pp. 131-144.

Table 1. Model Estimation Results

	MODEL 1 NO CH, NO SD	MODEL 2 CH, NO SD	MODEL 3 SD, NO CH	MODEL 4 SD AND CH	MODEL 5 RANDOM SD AND CH
	NL	PMNL	NL	PMNL	PMNL
α_{BUY}	-3.6115	-3.9085	-4.0632	-4.2374	-4.3157
	(-70.51)	(-56.39)	(-81.80)	(-61.05)	(-62.93)
α_{ORG}	-0.4151	-0.6758	-0.6557	-0.8038	-0.8640
	(-7.31)	(-9.28)	(-16.32)	(-10.28)	(-10.31)
β_{PRICE} (c)	-0.4173	-0.7655	-0.3525	-0.7416	-4.4995
	(-35.54)	(-21.03)	(-29.00)	(-21.10)	(-31.63)
β_{SD1}			5.1842	2.3662	2.3818
			(61.04)	(18.138)	(18.07)
β_{SD2}			8.0345	2.7474	2.4501
			(44.34)	(15.00)	(13.14)
σ_{BUY}		0.8974		0.7021	0.7436
		(29.39)		(24.99)	(29.34)
σ_{ORG}		0.9447		0.9005	1.0041
		(13.66)		(12.79)	(12.65)
s		0.2596		0.1604	
		(15.48)		(7.092)	
σ_{SD1}					0.0573
					(0.402)
σ_{SD2}					0.5503
					(5.008)
λ	0.5057	0.3912	0.7426	0.5432	0.5650
	(10.12)	(13.36)	(29.68)	(16.93)	(17.14)
NOBS	84317	84317	84317	84317	84317
NP	768	768	768	768	768
LL(EST)	-37376.29	-32411.03	-33061.71	-32093.50	-32062.47
ρ	0.5907	0.6451	0.6380	0.6486	0.6489
Adj. ρ	0.5907	0.6452	0.6380	0.6487	0.6490
LR tests	-	Restrict Model 2 to 1	Restrict Model 3 to 1	Restrict Model 4 to 2	Restrict Model 5 to 4
Chi-square	-	9930.52	8629.16	635.06	62.06
Result	-	Reject	Reject	Reject	Reject

Notes: t-ratio is reported inside the brackets. CH stands for consumer heterogeneity, and SD stands for state dependence. The log-likelihood of a model where all the parameters are restricted to 0 is -91319.53. All these models are significant by likelihood ratio test against the null model. The ρ is computed as 1-(LL(EST)/LL(NULL)) and adjusted ρ is computed as 1-((LL(EST)-No.Param)/LL(NULL)).

Figure 1. Nesting Structure