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ESSAYS ON ORGANIC FOOD MARKETING IN THE U.S.

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ESSAYS ON ORGANIC FOOD MARKETING IN THE U.S.

DISSERTATION

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the College of Agriculture, Food and Environment at the University of Kentucky

By
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Lexington, Kentucky

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2017

ABSTRACT OF DISSERTATION

ESSAYS ON ORGANIC FOOD MARKETING IN THE U.S.

This dissertation examines organic food marketing from three aspects: household demand for organic food, household choice of retail formats accounting for preference organic food preference, and farmers' joint adoption of organic farming and direct marketing methods. In Chapter Two, given the fast growth of private label milk and organic milk in the U.S., we estimate a censored demand system to study the demand relations among types of milk differentiated by brand types and organic status, using recent Nielsen Homescan data. We find that sociodemographic factors still play important roles in a household choice of milk types, and fluid milk is an inferior good. Moreover, as income increases, households are more likely to shift from buying conventional milk to organic milk and from private label conventional milk to branded conventional milk, as indicated by the asymmetric cross price elasticities.

In Chapter Three, we examine whether households' preference for organic food can affect their retail format choices for their grocery shopping trips. We model households' choices of five major retail format with a conditional logit model, also using the Nielsen Homescan data. Our main findings are that regular organic user households are more likely to patronage organic specialty stores and discount stores, but less likely to shop in warehouse clubs. Price, consumer loyalty, and household shopping behavior also affects household retail format choice.

In Chapter Four, we examine the relation between farmers' adoption of organic farming and direct marketing, given their similar objectives in satisfying consumer demand and increasing farm income. We model farmers' adoption of the two practices with a bivariate simultaneous linear probability model using data from USDA Agricultural Resource Management Survey. Our main finding is that the farmers' adoption of organic farming decreases their probability of adopting direct marketing, whereas the reverse effect is insignificant. Also, organic farming is found to improve gross farm income.

KEYWORDS: Organic Food, Private Label, Retail Format,
Direct Marketing, Demand System, Discrete Choice

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ESSAYS ON ORGANIC FOOD MARKETING IN THE U.S.

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Chapter 1 Introduction

Background

The organic food market has been experiencing substantial growth over the past decades in the United States. The total organic sale has maintained a double-digit growth since the 1990s, reaching a record level of 43.3 billion dollars in 2015 (Organic Trade Association, 2016). Also, once exclusive to organic specialty stores and natural food stores, organic food is becoming more widely available in main stream retailers. It is estimated that organic product is present in over 75% of all categories in supermarkets (Organic Trade Association, 2016). On the supply side, organic production is also expanding. In 2014, 14093 certified or exempt farms produced organic food, covering a total area of 3.7 million acres, and an additional 170 thousand acres are in transition to organic production (USDA, 2014).

Numerous factors have contributed to the rapid rise of organic food and organic farming. First, consumers' high demand for organic food plays a leading role. As consumers are increasingly concerned about food safety, nutrition and environmental degradation associated with conventional food production systems, organic farming provides an alternative due to its restrictions on the usage of synthetic pesticide and chemicals. Moreover, given the strong demand and high price premium of organic food, producers are incentivized to convert to organic production. Likewise, retailers are also motivated to expand their organic offerings in their stores.

USDA policies are critical in promoting organic agriculture. As early as 2002, the National Organic Program (NOP) was established to regulate organic product certification and labeling at the federal level, which is essential for the organic market due to the credence attribute nature of organic food. Moreover, the financial assistance for organic certification and funding for organic research has steadily increased over each of the last three Farm Bills, reaching 57.5 and 100 million dollars respectively in the 2014 Act (USDA, 2016). Given the current state of demand, supply, and policies in the organic sector, the U.S. organic food market is expected to maintain this growth trend.

Objective and Structure

It is noteworthy that the organic industry is in a dynamic marketing environment, and current knowledge of the organic sector is based on treating the organic food market in isolation from the marketing environment. Specifically, few studies of organic food demand account for the rise of private labeling and other important marketing trends, which could have potential impacts on the organic food market. Also, most studies on organic demand do not account for the retailing sector in their analysis. This might be inappropriate given consumers' differing perceptions of retail formats, and the increasing availability of organic food across all mainstream retail formats. Moreover, in parallel to the organic movement, local food is becoming increasingly popular among U.S. consumers, and thus direct marketing becomes an important marketing venue for farmers. An important question ignored in the current studies is what is the relation between farmers' decisions to adopt direct marketing and organic farming, given their substantial overlapping implications and motivations.

This dissertation aims to bring the missing marketing environment elements in the understanding of organic marketing by examining the three questions outlined above in three essays. Each essay is described in one chapter. Chapter Two examines U.S. household demand for milk differentiated by its organic status and brand types. An augmented almost ideal demand system accounting for the censoring of dependent variables and the endogeneity of milk expenditure is estimated, and corresponding price and income elasticities are calculated. The data source is the Nielsen Homescan consumer panel data in 2013.

Chapter Three focuses on the retail sector and examines whether consumers' preference for organic food would affect their choices of retail formats in their grocery trips. A conditional logit model is estimated to answer the question, and price levels in each format, consumer loyalty to each format, and other household factors are also controlled. The data source is the Nielsen Homescan consumer panel in 2013 and 2014.

Chapter Four, from the perspective of farmers, examines the relation between farmers' adoption of organic farming practice and direct marketing practice. A simultaneous bivariate linear probability model is estimated to answer the question, and the data is from the Agricultural and Resource Management Survey from USDA. Based on the modeling of practice adoption, the effects of the two practices on gross farm income are additionally examined.

Chapter Five summarizes the main findings and their implications from this dissertation. Areas for further research are also discussed.

Chapter 2 Organic Labeling, Private Label, and U.S. Household Demand for Fluid Milk

Introduction

The agri-food markets in the U.S. have experienced two noteworthy trends in the recent decade. First, private label products (store brands owned by the retailers, PL hereafter) are experiencing strong growth, making substantial inroads in numerous consumer packaged goods markets. It is estimated that the total market share of PL goods reached 14.6% in dollar sales and 17.2% in unit sales by 2013 (IRI, 2013), though substantial share differences exist across product categories, ranging from around 4% for rice and desserts to over 60% for frozen fruits and milk in 2012 (Hennessy, 2014). One notable feature of the PL goods is that they are generally sold at discounted prices compared to national brand goods, and this is confirmed in numerous hedonic price analyses (see Roheim, et al., 2011 for seafood in the UK; Smith, et al., 2009 for fluid milk in the U.S.). Nevertheless, according to recent consumer reports, the majority of consumers think that the quality of PL products has improved and they perceive private labels favorably (IRI, 2013; Nielsen, 2014).

A second trend is the increasing adoption of new production practices. As consumers' concerns over food safety, environmental degradation, and social injustice associated with conventional food production systems grow, the food industries are quick to adopt alternative production practices to assuage these concerns. Examples include producing fresh fruits and vegetables without using synthesized fertilizer, pesticide or GMO components (organic produce), harvesting tuna without bycatching dolphin (dolphin-free tuna) and paying a fair wage to coffee farmers (fair-trade coffee), (see Golan, et al., 2001 for more). Because consumers are not able to observe or infer the production process even after consumption, certification processes are usually established to verify the adoption of the new production practices, and this information is communicated to consumers via labeling schemes. Private labels and alternative production practices offer consumers additional choices, and importantly, they also represent evolutions in the production differentiation strategies in the agri-food industries (Gaviglio, et al., 2015). A good understanding of the demands of foods differentiated by private labels and production practices could facilitate the food industries in evaluating current product differentiation strategies and possibly contribute to the discovery of new strategies.

The U.S. fluid milk market provides an interesting case to study against this backdrop. On the one hand, fluid milk has gained the largest PL share of more than 60% among all product categories in 2012 (Hennessy, 2014). On the other hand, organic production practices have been employed by an increasing number of dairy farmers, and organic milk sales have been steadily increasing, reaching 2.1 billion pounds in 2011 (Schultz, 2013). Furthermore, retailers have gradually increased their offering of organic milk, once dominated by the national brands, under their own private labels (Dimitri and Oberholtzer, 2009). These changes in the U.S. fluid milk market also suggest dynamics in competition between branded and PL milk as well as between organic and conventional milk. Given this background, a potentially important question of industrial implication is: "What are the demand relations among milk differentiated by organic status (organic vs. non-organic) and brand type (branded vs. private label)?" The answer to this question could provide critical information for milk producers in deciding whether to adopt organic production practice, and it could also help milk producers, and retailers in formulating their brand strategies. We aim to answer the above question by estimating own and cross price elasticities of milk categorized by organic status and brand type in the framework of an Almost Ideal Demand System (AIDS). Additionally, the methodology also allows us to examine the expenditure elasticities and factors affecting the household choice of different milk types. This information can also be used to design effective milk marketing programs.

The remainder of this article is arranged as follows: Section 2 briefly reviews recent studies on demand for milk. Section 3 describes the data used in this study, which is then followed by a discussion of the AIDS model and related specification issues in Section 4. Section 5 presents and interprets the results, and Section 6 presents the conclusions.

Literature Review

Fluid milk has received substantial attention in the food marketing literature. One primary line of research focuses on the price premium of milk produced under alternative production practices, especially organic production. Experimental methods have widely been used to estimate consumers' willingness to pay (WTP) for the production attributes, and a recent study can be found in Bernard and Bernard (2009). More recently, researchers have begun to incorporate important factors previously ignored in their experimental design. Akaichi, et al. (2012) cautioned that consumers' exposure to organic farming information could affect their WTP for organic milk. In contrast to the above stated preference approach, hedonic analyses use actual market transaction data to estimate the implicit price of product attributes. Organic milk is found to carry a positive price premium (see Jaenicke and Carlson, 2015; Smith, et al., 2009).

The second line of research directly models the milk demand, and routinely calculates income and price elasticities. Alviola and Capps (2010) estimated the demand of organic and conventional milk in the U.S. market with a Heckman selection model. They found that organic milk is a normal good, and is price-elastic. Also, organic milk demand is more sensitive to conventional milk price than vice versa, demonstrating an asymmetric substitution pattern. The single equation approach, however, does not further differentiate milk based on other potentially important milk attributes besides organic, and therefore a demand system is appropriate. Chang, et al. (2011) categorized milk based on fat contents and organic claims, and estimated an AIDS model for inner city and suburban residents in Ohio. They found that suburban residents' demand for all milk type is price-inelastic; in contrast, inner city residents' demand for conventional whole and 2% milk, which constitute 89% of their milk expenditure, is price-elastic. These results suggest different purchasing patterns between inner city and suburban dwellers.

As mentioned above, PL milk offers consumers an economical choice, and it has also exerted a strong impact on the dynamics of the milk market. However, PL milk has rarely been included in previous discussions of the milk demand system, with three exceptions. Hovhannisyan and Gould (2012) studied the demand relations for leading national brand milk, other national brand milk, and PL milk in a generalized quadratic demand system (GQAIDS). They found elastic demand for other national brand milk which might be attributed to the high concentration of specialty milk (including organic) in other national brand milk. Additionally, an asymmetric substitution pattern existed among the three types. They also cautioned that their product categorization was based only on the brand type, while leaving out important health attributes of milk, which may not accurately represent consumer preference. Jonas and Roosen (2008) studied the demand for conventional PL milk, conventional branded milk, and organic milk in Germany with a censored demand system. One of their key findings was that organic milk demand was highly price elastic. They argued that this could be because their dataset did not include specialized organic stores, and thus most consumers were occasional buyers of organic, who tended to be price sensitive. They further cautioned the demand for organic milk could collapse due to high organic premium. Schrock (2012) offered an update of the above analysis with a new dataset in Germany. One interesting change she identified is that organic milk demand became price-inelastic, possibly because the German organic milk market matured during the study interval.

To the best of our knowledge, no study focusing on the demand relations of milk categorized by brand type and organic status has been conducted. It is important to study milk at a disaggregated level given the rapid growth of PL milk and organic milk in the past decade in the U.S. This paper contributes to the understanding of the demand for milk accompanying the rise of private label and organic production in the U.S. agri-food industry. Methodologically, we augment our demand system by including a reduced form total expenditure equation to address the endogeneity of total expenditure, an issue plaguing numerous demand system studies with cross section household data.

Data

The Nielsen Consumer Panel Dataset of U.S. households is the data source. According to Nielsen, this database consists of a representative panel of more than 40,000 U.S. households who provide information about their purchases intended for personal, in-home use from all major retail outlets. Each panelist household is requested to scan the UPC barcode of the purchased items with an in-home scanner provided by Nielsen so that the detailed information about the product characteristics can be recorded. Through this procedure, organic milk can be identified by its USDA organic seal on the containers. Also, the distinction between PL milk and branded milk can be drawn from the brand code. Besides product characteristics, Nielsen also collects sociodemographic information about panelist households.

We use the recently released Nielsen Consumer Panel Data 2013 to answer our research question above. We include refrigerated fluid milk in the analysis, and it is differentiated based on the brand type and organic status. This categorization yields four types of milk, viz. PL organic, PL conventional, branded organic and branded conventional milk. However, the market share of organic milk is still small despite the rapid expansion of organic farming in recent years. As shown in Table 2.1, only around 8% of households have bought organic milk at least once in 2013. Thus, we combine the PL organic and branded organic into one organic milk group. We further aggregate the purchase of these three types of milk by the panelists over 2013. Prices of milk are not directly recorded by panelists but can be calculated as unit values from total expenditure and total quantity. For households with zero purchases of some milk types, we follow the common practice in empirical literature by imputing the household missing prices with average prices of those types of milk in the Scantrack markets in which the households reside (Dong, et al., 2004; Yen and Huang, 2002).

Two additional considerations involve the choice of panelists in the analysis. First, that some panelists did not purchase certain milk type, particularly organic milk, might be due to the unavailability of that milk type in their nearby marketplaces. We, therefore, limit our panelist households to those located in main Nielsen Scantrack markets where censoring caused by product unavailability can be minimized. Second, since milk is perishable over time and it has a high purchase frequency, we further limit our samples to those households which purchased milk of any type at least once every month for at least ten months in 2013. In doing so, we can obtain a sample of households with a stable demand for milk. As a result, a final sample of 24,861 households is obtained.

Table 2.1 gives the sample statistics of the expenditure, quantity, price, and expenditure shares of conventional PL, conventional branded, and organic milk. As mentioned previously, organic milk is only purchased by a small fraction (7.62%) of the frequent milk buyers, whereas most households either buy conventional PL milk (93.32%) or conventional branded milk (67.15%), reflecting the major role of conventional milk on the market. It also needs to be noted that roughly 60% of the households buy more than one type of milk; many households simultaneously choose PL and branded milk. This conventional milk dominance is further reflected in the expenditure shares, with most of the fluid milk expenditure (96.16%) devoted to conventional milk. Despite its small market reach and expenditure share, organic milk is by no means negligible in the milk market. Organic milk price is almost double that of conventional milk, indicating a substantially high price premium compared with conventional milk. Moreover, among organic milk buyers the average expenditure on organic milk is 78.18 dollars, almost as high as that of the dominant PL milk. Last, the price of PL milk is lower than the branded milk, reflecting the typical low price strategy of the private label.

The household demographic variables potentially affecting milk purchases are described in Table 2.2. Household economic conditions are summarized in the income quantile and in share-of-purchase in discounted stores which could have significant effects on the choice and consumption level of milk. Wealthy households might be able to spend more on organic milk. The presence of small children at home is likely to prompt the consumption of organic milk which is generally considered to be more safe and nutritious than its conventional counterpart. The milk choice could also demonstrate differences across race and geographic region. Lastly, a larger household may consume more milk, thereby contributing to a significant milk expenditure. Note that this sample of households may no longer be representative of the entire U.S. population. However, the data-cleaning process satisfies our purpose since we aim to model the milk demand of stable milk-consuming U.S. households.

Econometric Specification

The Linear Approximated Almost Ideal Demand System (LA/AIDS) model proposed by Deaton and Muellbauer (1980) is used in the following analysis. Derived from a price-independent generalized logarithmic (PIGLOG) cost function, the LA/AIDS model has a flexible functional form that provides an arbitrary first-order approximation of any demand system. Additionally, it satisfies the axioms of choices and aggregation across consumers and allows for testing or for imposing theoretical restrictions. Therefore, it has been widely used in empirical demand system analysis.

Since there are no close substitutes for fluid milk, it is assumed that expenditure on demand for milk is weakly separable from other purchases (Dhar and Foltz, 2005), conditional on which the demand system is specified as:

$$w_i = \alpha_i + \sum_{j=1}^{n} \gamma_{ij} \log p_j + \beta_i \log(M/P),\ i = 1,2,\ldots,n \tag{1}$$

where w_i is the expenditure share of milk type i, p_j is the price of milk type j, and M is the total expenditure on milk. Price index, log P, is often approximated by the Stone price index. However, the Stone price index is not invariant to units of measurement (Moschini, 1995) and we correct the index by replacing the weights with the average expenditure share of the milk types, such that

$$\log P = \sum_{i=1}^{n} \overline{w}_i \log p_i. \tag{2}$$

In addition, household sociodemographic variables are incorporated into the model following the demographic translating approach proposed by Pollak and Wales (1981) and α_i takes the form:

$$\alpha_i = \alpha_{0i} + \sum_k \rho_{ik} d_k \tag{3}$$

where α_{0i} is a constant, and d_k are sociodemographic variables of the households. The consumer theory implies a set of restrictions on the demand system, viz. homogeneity, symmetry and, adding-up, and they can also be tested or imposed on the model parameters as:

$$\sum_{i=1}^{n} \alpha_{0i} = 1, \sum_{i=1}^{n} \rho_{ik} = 0, \sum_{i=1}^{n} \beta_i = 0, \sum_{i=1}^{n} \gamma_{ij} = 0 \ \text{(adding-up)} \tag{4a}$$

$$\sum_{j=1}^{n} \gamma_{ij} = 0 \ \text{(homogeneity)} \tag{4b}$$

$$\gamma_{ij} = \gamma_{ji} \ \text{(symmetry).} \tag{4c}$$

Censored Demand System and Two-Step Estimation

One characteristic of the scanner data is the presence of a vast number of zero purchase households for most products. This presents challenges for studying the demand for those products, since the censoring of the dependent variable could lead to sample selection, resulting in an inconsistent and biased estimation of demand equations.

In a single equation setting, this issue is routinely addressed with the application of the Heckman selection model (Heckman, 1979). In a system of equations, however, accommodating the censoring issue is more complicated. In the literature, the Amemiya-Tobin approach is widely followed, and numerous specifications and estimation strategies are based on this approach. We also focus on this approach.

Following Wales and Woodland (1983), one can denote the latent expenditure share w_i^* of milk type i such that

$$w_i^* = f_i(\mathrm{x}, \theta_i) + u_i \tag{5}$$

where $f_i(\mathrm{x}, \theta_i)$ is the deterministic expenditure share described in equations (1), (2) and (3); x and θ_i are the variable vector and the comfortable parameter vector in the demand system, respectively. Due to consumers' errors to maximize utility, errors to measure of the observed shares, or random disturbances, a normally distributed error term, u_i, is added to each of the deterministic shares. Further, to ensure that the observed shares lie between zero and one and sum up to one, a mapping from the latent share w_i^* to the observed share w_i is made such that

$$w_i = \begin{cases} 0 \quad , & w_i^* < 0 \\ \dfrac{w_i^*}{\sum_{i=1}^{3} w_i^*}, & w_i^* \geq 0. \end{cases} \tag{6}$$

In doing so, the observed shares are assumed to follow multivariate truncated normal distribution, and maximum likelihood estimation (MLE) is used to estimate this censored demand system. Alternative estimation methods based on simulated maximum likelihood estimation are proposed in Yen, et al. (2003) and Dong, et al. (2004). However, in these methods, the difficulty of evaluating multiple-level integrals of probability density functions prevents their applications in the empirical literature.

Instead of assuming the observed shares follow multivariate truncated normal distribution, an alternative specification to accommodate censoring involves adding a selection mechanism to equation (5) such that

$$w_i = \begin{cases} 0 \qquad\qquad\qquad\quad , & z'\tau_i + v_i < 0 \\ w_i^* = f_i(\mathrm{x}, \theta_i) + u_i, & z'\tau_i + v_i \geq 0 \end{cases} \tag{7}$$

where z is a vector of variables affecting consumers' decision to purchase milk i, and τ_i is a comfortable parameter vector. Pudney (1989) suggests that only personal characteristics should appear in the selection equation, and z is thus specified to contain only household sociodemographic variables. The error terms v_i and u_i are assumed to be bivariate normal distributed and the covariance of the errors $cov(u_i, v_i) = \delta_i$.

The system of equations in (7) can also be estimated using MLE, which is equally computationally prohibitive. To avoid this difficulty, we follow the two-step procedure proposed by Shonkwiler and Yen (1999) (SY hereafter) which gives consistent parameter estimation. Due to its simplicity, this method remains an attractive alternative to the MLE despite that it is less efficient than the MLE (Yen and Lin, 2006).

Shonkwiler and Yen (1999) derive the unconditional mean of the expenditure share for milk type i such that

$$E(w_i) = \Phi(z'\tau_i) f_i(\mathrm{x}, \theta_i) + \delta_i \phi(z'\tau_i) \tag{8}$$

and their procedure involves two steps: first, estimate the probability of positive expenditure share for each milk type i in a probit model and obtain the MLE estimator $\hat{\tau}_i$ of τ_i. Second, calculate $\Phi(z'\hat{\tau}_i)$ and $\phi(z'\hat{\tau}_i)$ for each i and estimate θ_i and δ_i in

$$w_i = \Phi(z'\hat{\tau}_i)f_i(\mathrm{x}, \theta_i) + \delta_i\phi(z'\hat{\tau}_i) + \eta_i \tag{9}$$

with MLE or seemingly unrelated regression (SUR). The inefficiency of this procedure is due to the heteroscedastic error η_i in (9), and the suggested weighted system estimator therein is a generalized least square (GLS) estimator that accounts for heteroscedasticity.

An additional complication with this procedure is the theoretical restriction of adding-up. Even though homogeneity and symmetry can be imposed similarly as in the original LA/AIDS model with (4b) and (4c), the adding-up restriction (4a) does not hold in the censored demand system because there is no guarantee that the deterministic part of w_i in (9) adds up to one across all i. Therefore, adding-up cannot be imposed by restricting the model parameters (Yen, et al., 2003). Pudney (1989) proposes treating one category of good as the residual category whose expenditure is the difference between total group expenditure and expenditure on all other categories in the group. This adding-up identity implies relations between elasticities of the residual category and other categories in the group (as shown below). Elasticities of the residual category can be calculated from elasticities of other categories so that the theoretical restrictions implied by adding-up can be met (Yen, et al., 2003). In this paper, we follow this approach. First, we estimate the system of equation (9) with one equation dropped and with homogeneity and symmetry imposed. Then the uncompensated own price elasticities (e_{ii}), uncompensated cross price elasticities (e_{ij}), and expenditure elasticities (e_{im}) of the milk types i in the remaining equations can be calculated from the estimated coefficients as:

$$e_{ii} = \left(\frac{\partial E(w_i)}{\partial \log p_i}\right)\left(\frac{1}{E(w_i)}\right) - 1 = \Phi(z_i'\hat{\tau}_i)\left(\frac{\hat{\gamma}_{ii}}{\bar{w}_i} - \hat{\beta}_i\right) - 1 \qquad (10)$$

$$e_{ij} = \left(\frac{\partial E(w_i)}{\partial \log p_j}\right)\left(\frac{1}{E(w_i)}\right) = \Phi(z_i'\hat{\tau}_i)\left(\frac{\hat{\gamma}_{ij} - \hat{\beta}_i \bar{w}_j}{\bar{w}_i}\right) \qquad (11)$$

$$e_{im} = \left(\frac{\partial E(w_i)}{\partial \log m}\right)\left(\frac{1}{E(w_i)}\right) + 1 = \Phi(z_i'\hat{\tau}_i)\frac{\hat{\beta}_i}{\bar{w}_i} + 1. \qquad (12)$$

The compensated own and cross price elasticities (e_{ij}^c) can be calculated using the Slutsky equation:

$$e_{ij}^c = e_{ij} + e_{im}E(w_j). \qquad (13)$$

The adding-up restrictions imply:

$$\sum_{i=1}^n w_i e_{ij} = -w_j, \sum_{i=1}^n w_i e_{ij}^* = 0,\ \sum_{i=1}^n w_i e_{im} = 0 \qquad (14)$$

from which the price and expenditure elasticities of the residual milk type can be calculated. All the elasticities are calculated at the sample mean. Also, for statistical inference, the standard errors of the elasticities are calculated with the delta method.

It needs to be noted that the above approach for accommodating adding-up restriction is variant to the equation dropped. We first estimate the system dropping the organic milk equation. And we re-estimate the system by dropping one of the remaining milk equations to recover the sociodemographic parameters in the organic milk equation. Either option yields a comparable parameter estimation.

Price and Expenditure Endogeneity

Price and expenditure endogeneity are prevalent in demand system analysis, which tends to render the estimation biased and inconsistent. A conventional solution to endogeneity is the instrumental variable approach, although difficulty remains in finding the appropriate instrumental variables for price and expenditure. The endogeneity issue in this analysis is briefly discussed.

Prices in the demand system analyses, instead of being observed directly, are usually calculated as unit values. And the variation of the unit values across households is comprised of both the variation of exogenous prices and the variation of potentially endogenous quality (Nelson, 1991). The endogenous quality can be explained by the simple fact that households tend to simultaneously determine purchasing quantity and quality in shopping trips. As a result, price calculated as unit value is likely to be endogenous. Cox and Wohlgenant (1986) proposed to use household characteristics as proxies for quality and to calculate the quality-adjusted price to approximate the exogenous price. Recent application of this technique can be found in Fourmouzi, et al. (2012). However, even though quality effects can be excluded from the unit value, leaving only price effect, the interpretation of the estimated parameters of the adjusted prices in the demand functions is still unclear at best since the dependent variables, purchasing quantity, cannot be adjusted for quality differences. Therefore, this approach is not followed here. We argue that the effect of potential price endogeneity on estimation could be minimal. Despite the efforts to engage in production differentiation in the fluid milk market, the differences among different types of milk are relatively small compared with many other foods. This limited degree of differentiation also explains the rise of PL milk and the increasing supply of organic milk under private labels.

Similarly, the expenditure endogeneity lies in the simultaneity of deciding the quantity demanded for each milk type i and the total expenditure on milk. To address the total expenditure endogeneity, we choose to specify a reduced form total expenditure equation to augment the demand system in (7) and to jointly estimate them as a system (see Dhar, et al., 2003; Xiong, et al., 2014). The total milk expenditure is explained by all sociodemographic variables and the price index in the demand equations. We also include household income and size in the explanatory variables as identifying instruments. The resulting reduced form equation for total milk expenditure is:

$$\log M = z'\kappa + \rho \log P + \theta income + \chi hhsize \tag{15}$$

where κ is a vector of sociodemographic variables explaining the total expenditure on milk, and z is the corresponding conformable parameter vector. P, as above, is the price index of milk and ρ is the coefficient of the price index.

To sum up our empirical specification, we drop the organic milk type and estimate a system comprised of the private label milk and branded milk share equation in (9) and the milk expenditure equation in (15) with full information maximum likelihood (FIML) in SAS procedure proc model. Then equations (10) – (14) are used to calculate elasticities for all milk types.

Results and Discussion

The estimation results from the first step probit models are presented in Table 2.3, and they show that different milk types have distinct consumer profiles. First, households with above-median income are more likely to purchase organic milk than households with below-median income. In addition, the higher the income, the more likely the household will purchase organic milk. By contrast, income level seems to negatively affect the likelihood of households purchasing PL conventional milk, while its effect on purchases of branded conventional milk is small. These findings suggest that households tend to substitute PL conventional milk for organic milk as income increases, and are in line with the notion that organic buyers are generally wealthier. Further, shares of household purchasing at discount stores is shown to negatively affect the choice of organic milk, but positively affect the choice of conventional milk. This result indicates the important role of income on households' choice of organic milk, given that wealthy households may have lower shares of purchase in discount stores. It may also suggest the limited availability of organic milk in discount stores.

Household demographic status plays important roles in the choice of different types of milk. The presence of children under six contributes to organic milk purchases, whereas it reduces the likelihood of purchasing private label milk. This finding may reflect the image associated with organic milk, that of premium nutrition and safe quality. Moreover, elderly households are less likely to buy organic milk, and this result is consistent with the preference for organic milk among young households. In addition, elderly households are more likely to purchase branded conventional milk and less likely to purchase PL conventional milk. This is intuitive since senior citizens may have special nutritional needs which can be met with food fortification in branded milk, whereas PL milk has little product differentiation. Additionally, higher-educated households are more likely to switch from buying conventional milk to organic milk since they might be better informed about the benefits of organic milk. Last, organic milk choices also differ across race and region. These findings are consistent with the characterization of organic consumers in recent studies. It needs to be noted, however, that organic consumer profiles differ across goods, time and markets under examination (Dettmann and Dimitri, 2009; Smith, et al., 2009; Zepeda and Li, 2007).

Based on the above probit estimation in the first step, the second step demand system estimation is presented in Table 2.4. The estimated coefficients of $\phi(z'\hat{\tau}_i)$ are significant for all milk types, indicating the presence of sample selection bias. Thus, the SY two-step estimation method is justified. The expenditure shares of branded conventional milk and organic milk are highly censored, and estimation bias could be severe if sample selectivity is not considered.

As expected, in the milk expenditure equation, as the household size increases, household expenditure on milk increases, and as the price index of the milk increases, households reduce their milk consumption, resulting in decreased milk expenditure. Interestingly, household milk expenditure decreases as the household income increases, suggesting that milk, as a group, is an inferior good. Given that a dominant share of total milk expenditure is on PL conventional milk (72.7%), this finding is consistent with Alviola and Capps (2010), who estimated a negative income elasticity of -0.01 for conventional milk. However, due to the categorical income in our analysis, calculation of the income elasticity for milk is beyond the scope of this paper.

A further examination of the expenditure elasticities in Table 2.5 shows the highest expenditure elasticity for PL milk (1.188), followed by branded milk (0.5), and organic milk (0.497). These expenditure elasticities are comparable to those in Dhar and Foltz (2005) and Jonas and Roosen (2008). They suggest that as household income increases, total expenditure on milk decreases, resulting in a significant reallocation of expenditure among the three types of milk. Expenditure is directed from PL conventional milk to organic milk and branded conventional milk, confirming – as pointed out above – substitution of PL conventional milk for organic milk.

Uncompensated and compensated price elasticities are also shown in Table 2.5. All elasticities are consistent with the demand theory. The highest uncompensated own price elasticity is found in organic milk (-2.455), followed by PL milk (-1.2), and branded milk (-1.169). High own price elasticities for organic milk are also often found in the literature (Hovhannisyan and Gould, 2012; Jonas and Roosen, 2008) and consumers tend to be price-sensitive to specialty milk, including organic.

All cross-price elasticities are positive, indicating that PL milk, branded milk and organic milk are, to a certain degree, substitutable. However, the substitutions among the three types of milk are evidently asymmetric. On the one hand, a 1% increase of PL milk price leads to 0.467% and 0.969 % increases in branded milk and organic milk demand, respectively. On the other hand, a 1% price increase of either branded milk or organic milk price does not significantly increase the demand for PL milk. A similar asymmetric substitution pattern can also be found between branded conventional milk and organic milk: a 1% increase of branded milk price leads to a 1.106% increase in organic milk demand, whereas a 1% increase of organic milk price merely contributes to a 0.202% increase in branded milk demand. One plausible explanation for asymmetric substitution is that once consumers have bought organic milk and perceive the benefits of it, they are unwilling to switch back to PL or branded conventional milk, demonstrating stickiness in consumer behavior (Dhar and Foltz, 2005). Asymmetry is also found in Chang, et al. (2011) and Jonas and Roosen (2008).

Conclusion

Recent decades have manifested two trends in the U.S. fluid milk market: the rise of private label milk and the growth of organic milk. Brand type and organic status have become two important attributes affecting consumers' milk-purchasing decisions. In addition to the price analysis studies that improve our understanding of consumers' preference for brand type and organic status, we directly model the demand for three types of milk – conventional private label, conventional branded and organic – in a censored demand system following the SY procedure. Factors affecting milk choice and demand are examined and price and expenditure elasticities are calculated to study the demand relations among these types of milk.

The main conclusions are as follows: sociodemographic variables are still important factors in explaining the demand for different types of milk. Based on these different consumer profiles, milk marketers can carry out more targeted marketing campaigns for various kinds of milk. More importantly, milk as a group is an inferior good, a conclusion which might be attributed to the fact that private label milk is an inferior good. Also, despite its small market share, organic milk seems to have strong market potentials; as income increases, substitution of private label conventional milk for organic milk can be identified. Retailers which provide private labels under their own brands especially need to explore the opportunities associated with organic milk. In addition, there also seems to be a tendency for consumers to substitute private label milk for branded milk. Product differentiation and invention could be essential for branded milk producers since, for them to compete with private label milk, their strength lies in addressing additional consumer needs and concerns beyond basic food safety and nutrition.

One drawback of this study could be the categorization of the milk. As stated in the data section, organic milk reach and average expenditure share is still small, and thus we combined the private label and branded organic milk as one group. This blurring of brand types in organic milk prevents us from studying the demand relation between the two groups of organic milk, and thus no conclusions can be drawn regarding the competition between private label and branded milk producers when milk is organic for both. However, as the organic milk sector continues to mature, further data may be used to shed light on this issue.

Tables

Table 2.1 Summary Statistics of Milk Consumption, Expenditure and Price

Variables	Mean	SD	% Consuming
Quantity (Gallons) - Consuming Households			
Conventional Private Label ($i = 1$)	27.30	26.63	93.32
Conventional Branded ($i = 2$)	10.47	16.55	67.15
Organic ($i = 3$)	11.42	14.80	7.62
Expenditure (Dollars) - Consuming Households			
Conventional Private Label	91.83	85.71	
Conventional Branded	40.81	62.87	
Organic	78.18	98.63	
Expenditure Share (%)			
Conventional Private Label	72.70	34.35	
Conventional Branded	23.46	31.77	
Organic	3.84	17.32	
Price (Dollar/Gallon)			
Conventional Private Label	3.68	0.99	
Conventional Branded	4.30	1.34	
Organic	7.01	0.60	

Note: Number of households in the sample is 24861.

Table 2.2 Summary Statistics of the Sociodemographic of the Sample Households

Variables	Definition	Mean	SD
$income1$	=1 if HH incomes falls below 25% (base)	0.19	0.39
$income2$	=1 if HH incomes falls in 25-50%	0.35	0.48
$income3$	=1 if HH incomes falls in 50-75%	0.3	0.46
$income4$	=1 if HH incomes falls in 75-100%	0.17	0.37
$discount$	Share of households purchase in discount stores	0.17	0.29
$child$	=1 if presence of children under 6	0.03	0.16
$age1$	=1 if HH head less than or equal to 40 (base)	0.07	0.26
$age2$	=1 if HH head is higher than 39 but less than 64	0.60	0.49
$age3$	=1 if HH head is higher than 64	0.33	0.47
$race1$	=1 if white HH (base)	0.87	0.33
$race2$	=1 if black HH	0.06	0.24
$race3$	=1 if Asian or other race HH	0.06	0.24
$edu1$	=1 if HH head education is high school graduate (base)	0.18	0.38
$edu2$	=1 if HH head education is some college	0.28	0.45
$edu3$	=1 if HH head education is graduated college or post college grad	0.54	0.5
$region1$	=1 if residing in Northeast (base)	0.21	0.41
$region2$	=1 if residing in Midwest	0.26	0.44
$region3$	=1 if residing in South	0.34	0.47
$region4$	=1 if residing in West	0.19	0.39
$hhsize$	Number of residents in a household	2.48	1.25

Table 2.3 First Stage Probit Estimation

	Private Label		Branded		Organic	
	Coef. (Std. err.)	M.E. (Std. err.)	Coef. (Std. err.)	M.E. (Std. err.)	Coef. (Std. err.)	M.E. (Std. err.)
income2	0.053 (0.036)	0.006 (0.005)	-0.006 (0.024)	-0.002 (0.009)	0.007 (0.039)	0.001 (0.004)
income3	-0.005 (0.038)	-0.001 (0.005)	-0.004 (0.026)	-0.001 (0.009)	0.126** (0.039)	0.015** (0.004)
income4	-0.043 (0.044)	-0.005 (0.005)	0.002 (0.030)	0.001 (0.011)	0.336** (0.043)	0.041** (0.004)
discount	0.192** (0.048)	0.024** (0.006)	0.236** (0.030)	0.084** (0.011)	-0.194** (0.046)	-0.025** (0.006)
child	-0.157* (0.077)	-0.019* (0.009)	0.029 (0.055)	0.011 (0.020)	0.405** (0.064)	0.053** (0.008)
age2	-0.005 (0.052)	-0.001 (0.006)	0.147** (0.033)	0.054** (0.012)	-0.122** (0.045)	-0.017** (0.007)
age3	-0.158** (0.054)	-0.019** (0.006)	0.195** (0.035)	0.073** (0.014)	-0.152** (0.048)	-0.022** (0.008)
edu2	0.005 (0.039)	0.001 (0.005)	-0.017 (0.026)	-0.006 (0.009)	0.166** (0.044)	0.016** (0.004)
edu3	-0.068 (0.037)	-0.008 (0.004)	-0.128** (0.025)	-0.046** (0.009)	0.374** (0.042)	0.045** (0.004)
race2	-0.218** (0.047)	-0.026** (0.006)	0.256** (0.036)	0.092** (0.013)	0.054 (0.048)	0.007 (0.006)
race3	-0.217** (0.048)	-0.026** (0.006)	0.047 (0.035)	0.017 (0.012)	0.230** (0.043)	0.030** (0.006)
region2	0.384** (0.034)	0.064** (0.006)	-0.381** (0.026)	-0.108** (0.007)	-0.104** (0.039)	-0.011** (0.004)
region3	0.415** (0.033)	0.066** (0.006)	-0.719** (0.025)	-0.227** (0.007)	0.207** (0.034)	0.027** (0.004)
region4	0.408** (0.038)	0.068** (0.007)	-0.640** (0.028)	-0.181** (0.006)	0.195** (0.038)	0.022** (0.004)
constant	1.294** (0.065)		0.794** (0.045)		-1.792** (0.066)	

Note: Standard errors in parentheses. ** and * indicate significant at 1% and 5% respectively.

Table 2.4 Second Stage Demand System Estimation

	Private Label	Branded	Organic	Milk Expenditure
log p_1	-0.051** (0.008)	0.036** (0.008)	0.094** (0.015)	
log p_2	0.036** (0.008)	-0.099** (0.01)	0.0796** (0.037)	
log p_3	0.015* (0.006)	0.063** (0.006)	-0.89** (0.04)	
log*(M/P)*	0.146** (0.007)	-0.173** (0.008)	0.071** (0.022)	
discount	-0.007 (0.01)	-0.104** (0.021)	-0.073 (0.048)	-0.004 (0.014)
child	-0.014 (0.015)	-0.025 (0.019)	0.032 (0.038)	0.106** (0.025)
age2	-0.002 (0.009)	-0.026 (0.017)	0.019 (0.025)	0.022 (0.016)
age3	0.023* (0.01)	-0.012 (0.02)	-0.006 (0.035)	-0.003 (0.017)
edu2	-0.0002 (0.007)	-0.005 (0.008)	0.013 (0.104)	-0.001 (0.012)
edu3	0.007 (0.007)	0.019 (0.012)	-0.002 (0.105)	0.005 (0.011)
race2	0.038** (0.011)	-0.047* (0.022)	-0.082* (0.039)	-0.297** (0.017)
race3	-0.003 (0.01)	0.025* (0.012)	0.06* (0.027)	-0.002 (0.016)
region2	0.02 (0.015)	-0.039 (0.03)	0.044 (0.042)	-0.033** (0.012)
region3	0.075** (0.015)	-0.01 (0.06)	-0.205** (0.032)	0.071** (0.011)
region4	0.066** (0.015)	-0.045 (0.053)	-0.083* (0.032)	0.001 (0.012)

(Continued)

Table 2.4 Continued

Variables	Private Label	Branded	Organic	Milk Expenditure
$\phi(z'\hat{\tau}_i)$	-0.68** (0.129)	-0.349* (0.172)	-0.212* (0.089)	-
income2				-0.028** (0.011)
income3				-0.052** (0.011)
income4				-0.055** (0.013)
log *P*				-1.181** (0.018)
hhsize				0.172** (0.003)
Constant	0.331** (0.035)	1.111** (0.07)	1.205** (0.23)	4.389** (0.033)

Note: Standard errors in parentheses. ** and * indicate significant at 1%, 5% respectively. Price and milk expenditure parameter estimation are not shown because these estimators cannot be readily interpreted. Organic milk equation parameters are estimated by dropping branded milk equation.

Table 2.5 Own and Cross Price Elasticities and Expenditure Elasticities Estimates

	Price Elasticities			Expenditure Elasticities
	Private Label	Branded	Organic	
Uncompensated				
Private Label	-1.20**	0.002	0.012	1.188**
	(0.011)	(0.01)	(0.008)	(0.009)
Branded	0.467**	-1.169**	0.202**	0.500**
	(0.027)	(0.028)	(0.018)	(0.022)
Organic	0.969**	0.990**	-2.455**	0.497**
	(0.122)	(0.125)	(0.167)	(0.115)
Compensated				
Private Label	-0.338**	0.281**	0.057**	
	(0.011)	(0.009)	(0.008)	
Branded	0.830**	-1.051**	0.221**	
	(0.022)	(0.028)	(0.018)	
Organic	1.331**	1.106**	-2.436**	
	(0.144)	(0.123)	(0.165)	

Note: Standard errors in parentheses. ** and * indicate significant at 1%, 5% respectively.

Chapter 3 Does Consumers' Preference for Organic Foods Affect Their Store Format Choices?

Introduction

Retail sales of organic food in the U.S. have increased rapidly, growing from 3.6 billion dollars in 1997 to 43.3 billion dollars in 2015, an 11 percent increase from previous year compared with the 3 percent growth rate of overall food sector (Organic Trade Association, 2016). The growth trend, however, varies across food categories, with fruits and vegetables the leading products, and they are typically the first organic products purchased by consumers new to organic products (Dettmann and Dimitri, 2009).

The high growth of organic food has generated substantial interests in understanding the organic food market. The sociodemographic profile of organic consumers and their motivations to buy organic food are extensively studied. A typical organic consumer is characterized as being wealthy, young, educated, and lives in the West region in the U.S. and he or she is motivated to buy organic food for better food safety, health benefits and environmental benefits (Hughner, et al., 2007; Nasir and Karakaya, 2014; Zepeda and Li, 2007). Also, the success of the organic sector hinges on whether the price premium of organic food can be realized to compensate for the higher production cost. Thus, a wealth of studies is devoted to evaluating the organic premium, and its existence is confirmed for numerous organic products with both stated and revealed preference methods (see Hu, et al., 2009 for WTP for organic blueberry jam; and Smith, et al., 2009 for organic fluid milk). Moreover, the demand for organic food itself has been widely studied, both independently or in a product group. (see Dettmann and Dimitri, 2009 for milk; and Zhang, et al., 2008 for fresh produce).

One factor that contributes to the high growth of the organic market is the wider availability of organic food in main-stream retailers (Organic Trade Association, 2016; Quagliani, 2015). As a result, competition has intensified in the retail sector, leading to retailers' forming strategic marketing plans for their organic food. For example, while Whole Foods Market had early success with natural and organic food, it introduced a smaller store format named Whole Foods 365, offering consumers a limited selection of organic products at a lower price (Strom, 2015). Moreover, Walmart announced its entry into the organic market in 2006 (Martin, 2014) and currently sells its organic brand Wild Oats at prices comparable to conventional food. Additionally, major discounter and club stores such as Aldi and Costco keep their pace with the organic trend by increasing their offering of organic food in their stores.

However, the retail sector receives inadequate attention in the current understanding of the organic food marketing, despite its important role in the supply chain. Because of their direct interaction with consumers, retailers have a better knowledge of consumer demand. With this knowledge, retailers can affect consumer demand for food including organic food with a combination of marketing mixes in store. Moreover, the intangible store image of retailers is an essential element in affecting consumer perception of products offered in store and thus indirectly affect their demand (Lee and Hyman, 2008). Therefore, as organic food retailing goes through major shifts, the current approaches which largely ignore the retail sector could lead to an incomplete understanding of the organic food marketing.

In this article, we aim to fill this gap by examining whether consumers' preference for organic food affects the types of store they visit for grocery shopping. The results have managerial implications for the retail sector in which stores of different formats compete intensely in the organic, and other food sectors as well. Also, for the organic food producers, processors and distributors, this study could offer some insights in their choosing marketing channels. A better understanding of the organic food retailing is likely to improve the effectiveness of subsequent USDA policies and programs aiming to promote organic food.

The remainder of this article is arranged as follows. Section 2 reviews studies on organic preference and store choice to further motivate our research. Section 3 discusses the methodology employed followed by data description in Section 4. Section 5 demonstrates the main findings of the empirical model followed by a discussion of these results. Lastly, Section 6 concludes.

Literature Review

We review two lines of literature. The first line of studies suggest relationship between consumers' organic food preference and their retail format choice. This forms the conceptualization base of this study. We further review studies modeling consumers' retail format choice accounting for their organic preference. This study is an extension along this line of research.

Organic Preference and Retailer Format

The relation between consumers' preference for organic food and the retail format choice in their grocery trips is frequently discussed in the literature. Thompson and Kidwell (1998) consider the possible linkage between consumers' two decisions—whether to buy organic food and whether to shop in cooperative or specialty grocery store—and model the two decisions jointly in a two-equation probit model. They find that local cooperative shoppers are more likely to buy organic foods and consumers with a high propensity to buy organic food are more likely to shop from cooperatives. Moreover, Ngobo (2011) models French consumers' organic food purchase behavior in a retail setting. By employing an incidence/brand choice/purchase quantity model, he finds that consumers are less likely to buy widely distributed organic brands, which are largely sold in conventional supermarkets and are often perceived to be of lower quality. This finding further implies that French consumers associate organic products with specific stores—particularly those organic specialty stores. These results suggest that consumers' preference for organic food could be positively related to their patronage of the organic specialty store, which is also supported from the perspective of stated preference.

With data from a consumer survey conducted in six traditional grocery stores and one specialty grocery stores spread across Ohio, Batte, et al. (2007) study the WTP for organic and other attributes of a breakfast cereal product. They find the WTP for the organic attribute is 50% higher for specialty grocery shoppers than traditional grocery shoppers, besides significant sociodemographic differences between the two types of consumers. Additionally, Wier, et al. (2008) examine the demand characters in Britain and Denmark, two mature organic markets, and find the large concentration of organic food consumers in Denmark express stronger confidence for organic foods sold in alternative retail channels, including specialist stores, farm gates, market stalls, and other direct marketing channels. Ellison, et al. (2016) further investigate the interaction of product type and retail context on consumers' evaluation of organic foods' taste, nutrition, safety and other attributes using an online experiment. As expected, they find the halo effect associated with organic food and more importantly, retail context is crucial in determining consumers' evaluation of organic food's attributes.

Retail Format Choice and the Role of Organic Preference

Consumers' retail format choice has been extensively studied since household scanner data become widely available. Current studies tend to focus on the role of retailers' marketing mixes while household sociodemographic status, consumer shopping behavior, and loyalty to particular store formats are also shown to have strong effects on consumers' retail format choice (Bell and Lattin, 1998; Fox, et al., 2004; Volle, 2001).

Few studies, however, account for organic consumer preference. Two exceptions are Staus (2009) and Hsieh and Stiegert (2012). Staus (2009) highlights the effects of households' attitudes towards organic food, environment, freshness, quality, pricing, and advertising on household retail format choice when they purchase fruits and vegetables. By estimating a mixed multinomial logit model with German Gfk scanner data, he finds that households reported to like organic foods are more likely to visit specialized organic stores, and less likely to visit conventional supermarkets. With a similar multinomial logit model and U.S. Nielsen scanner data from 2005 to 2008, Hsieh and Stiegert (2012) use households' percentage of organic food consumption in total food expense to proxy for households' preference for organic food and interact it with relative store price level, discount offering, and household income level to explain household retail format choice. They conclude that organic households' stronger quality perception affects their willingness to pay and price sensitivity in their choice of store formats.

We contribute to this line of literature by directly examining the effect of household organic preference on their choice of retail format. Staus (2009)'s measure of household organic preference is based on household self-reporting, which may not reflect the real organic preference, compared to our measure based on the purchasing history. The mechanism through which Hsieh and Stiegert (2012) assume organic preference affects store format choice is only through pricing or income effects; this ignores consumers' direct association of quality organic food with particular retail formats, as demonstrated in the previous studies. We also account for households' habitual patronage to certain retail format by introducing exponentially weighted loyalty indexes, pioneered by Guadagni and Little (1983). Further, we focus on households in California, the largest organic market in the U.S., and our analysis is more relevant to the current fast-changing U.S. organic market.

Methodology

The logit-type models based on the random utility theory have long been the workhorse in modeling discrete consumer choices. Consumers' retail format choice for grocery trips can also be modeled within this framework. Staus (2009), and Dong and Stewart (2012) study consumers' retail format choice for fresh produce and milk, respectively.

Conditional Logit Model with Repeated Choices

We follow a similar treatment and adopt the conditional logit model proposed by McFadden (1974). Given the panel structure of our data in which the entire grocery trips history is recorded for numerous households, McFadden's static model can be straightforwardly extended to allow for repeated household choices. According to the random utility theory, the utility household i derive from visiting retail format j in week t can be written as

$$u_{ijt} = V_{ijt} + \varepsilon_{ijt} \quad (1)$$

where V_{ijt} is the deterministic component, and ε_{ijt} is the random component. Households choose the retail formats that yield the highest utility for them in each week. Since both the attributes of the retail formats and characteristics of the households can affect household utility, we further specify a general form of the deterministic component of household utility such that

$$V_{ijt} = \alpha_j + \boldsymbol{\beta}\boldsymbol{X}_{jt} + \boldsymbol{\gamma}_j\boldsymbol{Z}_{it} \quad (2)$$

where $\boldsymbol{X}_{jt}$ is a vector of alternative-variant variables, representing the attributes of retail format j. The alternative specific intercept, α_j, captures all other attributes specific to retail format j, which could include store image and other unobservable attributes that are not controlled for. Some variables in $\boldsymbol{X}_{jt}$ vary over time. Moreover, $\boldsymbol{Z}_{it}$ is a vector of household characteristics, including household shopping behavior, sociodemographic status, and loyalty index to each retail format. $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}_j$ are the vectors of the unknown parameters.

Under the assumption that ε_{ijt} follow independent identical Type I extreme value distribution, it can be shown that the probability of household i visiting retail format j in week t is

$$\Pr(Y_{it} = j) = \frac{\exp(V_{ijt})}{\sum_{l=1}^{j} \exp(V_{ijt})}. \quad (3)$$

Given this derived probability and the history of households' retail format choices, we can estimate the conditional logit model of retail format choice with the maximum likelihood estimation (MLE). Denote $d_{ijt} = 1$ if household i visited retail format j in week t, and $d_{ijt} = 0$ otherwise; the log-likelihood function of consumer retail format choice is

$$lnL = \sum_{i=1}^{N} \sum_{j=1}^{J} \sum_{t=1}^{T} d_{ijt} \ln \Pr(Y_{it} = j). \quad (4)$$

From the estimated coefficients, the marginal effects of the explanatory variables on consumers' probabilities of choosing each retail format are calculated for interpretation.

Model Specification

We specify our model based on prior store choice and retail format choice studies. The utility households derive from patronizing one retail format is explained with four types of explanatory variables: retail format marketing mix, household sociodemographic status, shopping behavior, and household loyalty.

First, marketing mix has substantial effects on consumer retail format choice, as shown in the literature. Accounting for the limitation of our data, we focus on the pricing in each retail format and control for the price level in our model. On the one hand, the price level is the key consideration for households when having their grocery trips and the higher price is associated with a disutility for the households. Also, the competition among retail formats and the differences among them can be mostly reflected in their pricing. For example, big-box stores and other mass merchandisers offering substantially lower price than conventional grocery stores after controlling for the brand, quality and package size (Leibtag, 2006; Leibtag, et al., 2010). On the other hand, another marketing mix, such as product assortment, is also important in explaining consumers retail format choice, yet it is infeasible to accurately measure this marketing mix with our data.

Because many of the remaining retail marketing mixes stay relatively constant over time, we thus leave them to be absorbed into the retail-format-specific intercept.

The second category of explanatory variables characterize consumer shopping behavior. Our main interest is the effect of organic preference on retail format choice, and we define household organic preference as the percentage of organic produce and dairy products expenditure in total expenditure on these goods[1]. We expect household organic preference may influence its choice of retail format since different formats have distinct organic offerings and consumers' perception of the retail formats varies substantially.

Shopping cost could strongly affect consumers' format choice. A direct way to measure the shopping cost of one household is to measure the distances between the household and the nearest store of each retail format. Since retailers of different formats strategically locate in different areas (grocery stores are usually near the main residential areas while warehouse clubs are located farther away from the residential areas), the distances and thus the shopping cost can vary substantially across retail formats. However, due to privacy reasons, we cannot explicitly measure the distance. Instead, we construct a variable of household shopping frequency to approximate the shopping cost one household may face under the assumption that households with higher shopping costs are likely to shop less frequently than those with lower shopping costs.

Additionally, coupon usage is another important consumer buying behavior characteristic. Retail formats differ in their coupon offerings, resulting in two distinct pricing strategy: EDLP (everyday low pricing) and HILO (high/low pricing). Thus,

[1] Produce including fruits and vegetables and dairy products are chosen due to their major shares among all organic food categories.

consumer preference for these pricing strategies may be accounted for by their coupon use frequency during their shopping trips. Besides this shopping behavior, we also include essential household sociodemographic variables in our model. Households with different social demographic profiles have been observed to have a distinct preference in consumer choice studies and as discussed above, numerous academic and industrial research have been devoted to characterizing a typical organic consumer.

The last key variable in explaining households' retail format choice is households' loyalty to each retail format. Positive experiences from the past choices are passed down to future choice scenarios, prompting households to make the same choice. One direct approach to account for loyalty is to include the lagged choices in the deterministic component of the utility function (see Jones and Landwehr, 1988; Staus, 2009). Chintagunta, et al. (2001) further derived the conditions under which dynamic utility maximization behavior yielded the above model specification in a dynamic utility maximization framework. Alternatively, loyalty can also be accommodated with the loyalty indexes approach. In their seminal study of the household coffee brand and size choice, Guadagni and Little (1983) defined the brand loyalty variables as exponentially weighted sequences of previous purchases and they argued the loyalty variables capture the preference heterogeneity across households and preference change in the purchase-to-purchase dynamics.

Fader and Lattin (1993) pointed out that the variation in the loyalty variables does not distinguish between the preference heterogeneity across households and preference change over time, and in the event of an abrupt preference change, earlier choice history is irrelevant in predicting further choices. Based on a Dirichlet-multinomial model, they proposed a loyalty measure which could allow abrupt preference change. However, consumer choice for the retail format is less likely to experience sudden changes than the preference for brands due to the potentially higher cost of switching retail formats than switching brands. Thus we follow Guadagni and Little (1983) and construct similar loyalty index variables for each of the retail formats.

Data

Our data source is Nielsen Homescan from 2013 and 2014. Each year, Nielsen invites a vast and representative sample of U.S. households to record their purchases for personal and in-home uses by scanning the barcodes on the purchased products. Participating households are also asked to record information regarding the store and shopping trips. Though Nielsen does not provide names or the precise locations of the stores, retail formats of each store can be identified in the dataset which is sufficient for the purpose of this study.

The U.S. is one of the major organic food markets globally, and California is the leading state in organic sales and production in the U.S. (Klonsky, 2010). We choose households in California in our analysis to avoid the effects of the limited availability of organic food in some states on consumer retail format choice. Four major scantrack markets are defined by Nielsen in California: San Francisco, Los Angeles, San Diego and Sacramento. The 2013 data is used for initializing the retail format loyalty variable and generating shopping behavior variables[2], and only the 2014 data is used for model estimation. Additionally, we include only households making grocery shopping trips at

[2] It is plausible for consumers who prefer to patronize a particular retail format to demonstrate certain shopping behavior, resulting in endogenous shopping behavior if the same dataset is used to generate these shopping behavior explanatory variables and estimate the choice of retail format.

least once every month in 2013 and 2014 to ensure that households in the sample keep recording their purchase. Furthermore, we focus on households' main grocery trips, and we exclude shopping trips with only non-food item purchases and trips with less than five food item purchases. This results in a final sample of 1236 households and 49723 grocery trips.

Choice Set of Retail Formats

The Nielsen data contains 66 mutually exclusive retail channels, among which grocery store, discount store, warehouse club store, convenience store, dollar store, and drugstore are the mainstream retail formats. We focus on these mainstream retail formats.[3] Note that grocery stores differ substantially in their organic food offerings, and pooling all grocery stores into one choice is unlikely to reflect consumers' preference for grocery retail format. Stores like Whole Foods and Trader Joe's, for instance, are specialized in marketing organic and natural food. Hence, assuming that organic specialty grocery stores offer more organic varieties and generate more revenues from organic food sales, we divide grocery stores into two categories based on the share of organic produce and dairy sale to total sale in produce and dairy[4]: grocery stores with more than five percent of organic sale is categorized into the choice of organic specialty grocery stores and the remainder of the grocery stores are grouped as conventional grocery stores. Moreover, convenience stores, dollar stores, and drug stores are the marginal channels in

[3] Direct marketing channels including farmers' market, pick your own, door to door and CSA are gaining momentum in organic food marketing. However, the total sale through these venues is still small. Thus we do not include these direct marketing channels in our analysis.

[4] In contrast to our categorization approach, Hsieh and Stiegert (2012) used their own judgement to categorize stores into three types: value oriented retailers, supermarkets and high-end shops in a city with which they are familiar. While their approach may have some merits since it can identify more stores, it could introduce researchers' personal bias and it does not offer a systematic solution to study a large market area, such as the Californian market.

food retailing and offers a limited selection of organic food, we group these three retail formats into one choice and rename this group as the residual format. To sum up, households face five types of retailer formats: organic specialty grocery stores, conventional grocery stores, discount stores, warehouse clubs, and the residual format.

Table 3.1 describes the basic features of the five retail formats in the Californian food retail market in 2014. A first examination of the numbers of the retailer chains and stores reveals that the food retail sector in California closely resembles a competitive market with numerous retailers competing within and between retail formats. With its largest number of stores, the conventional grocery store is the leading format in food retailing, accounting for 60% of the total household store visits. By contrast, the organic specialty grocery store is substantially smaller in both store visit share and store accessibility. Discounter stores and warehouse have a similar market share in our data.

Product assortments also differ substantially across retail formats. While most items sold in both formats of grocery stores are food, conventional grocery stores offer more choices to consumers. Similar to conventional grocery stores, discount stores also carry a large assortment of goods, among which food only accounts for 46%. This is expected given the discounter strategy of satisfying consumer demand at one stop shopping. Warehouse clubs take a different strategy from discounter by offering a narrow product assortment yet most (76.6%) of the goods sold there are food. Since food is not the focus in the residual format, it carries a large assortment of goods while only 41.2% are food items. Regarding organic food marketing, it is expected that organic specialty grocery stores offer the most organic choices and generate the largest share of revenue from selling organic food. Though conventional grocery's organic share is half of that in organic specialty stores, it is still higher than the other retail formats. Interestingly, despite its limited selection of organic products in the store, warehouse club has a 6.1% share of organic sales, only after organic specialty stores. This might be a result of the bulk purchasing in warehouse clubs.

Explanatory Variables and Measures

To operationalize the explanatory variables in the previous chapter, we discuss the construction of these variables and measures in detail in this section. We also provide descriptive statistics for these variables.

Format Price Index To measure the price level in each of the retail format, we adopt a method similar to the one employed in constructing Consumer Price Index (CPI). A basket comprised of the twenty most frequently purchased product modules by the households (see Table 3.2) is first selected [5], and the total prices of this basket in each retail format and market are calculated. The price index is then calculated as the total price of the basket in each of the format normalized by the total price of the same basket in the market. Specifically, the price index takes the following form:

$$PI_{jmt} = \frac{\sum_{g=1}^{20} \bar{p}_{gjm}^{t}\, \bar{q}_{g}^{t}}{\sum_{g=1}^{20} \bar{p}_{gm}^{t}\, \bar{q}_{g}^{t}} \tag{5}$$

where $\bar{q}_g^t$ is the average quantity of household purchase of product g in week t in 2013. And $\bar{p}_{gjm}^t$ is the average price of product module g in format j in scantrack market m in

[5] If too few products are chosen, it is unlikely that the calculated price index would reflect the general price level in a retail format whereas if too many products are chosen, prices can be missing for some products in the basket in some retail formats, rendering the calculated price index inaccurate. We choose the twenty most purchased products to maintain a balance between the two scenarios.

week t in 2014 while $\bar{p}_{gm}^{t}$ is the average price of product module g in market m in week t in 2014. Note that the price indexes vary across format, market, and time.

The resulting price indexes are plotted in Figure 1. The price indexes show some similar patterns in the four scantrack markets. First, the price index is the highest in organic specialty stores, indicating price level in these stores are generally 1.5 and 2 times higher than the market price level. This is consistent with the high price premiums organic foods command. Except for the relatively low warehouse club price index in the San Francisco market, the format with the next highest price index is conventional grocery stores, followed by discount stores and other stores. Also, note that price index is relatively stable for conventional grocery stores because they have the largest share in food retailing and thus have the largest impact on the market price index used for normalizing price indexes. Similar stability is observed for the discounter, which might be a result of the every-day-low-price strategy adopted there. In contrast to conventional grocery and discounter, price indexes in the organic specialty store and the warehouse club have shown substantial changes over the weeks. The high-low pricing could be responsible for the fluctuation.

Household Shopping Behavior Table 3.3 summarizes the household shopping behavior and sociodemographic variables discussed above. We use the share of expenditure on organic produce and dairy products in the total expenditure on these products to measure household preference for organic food. A majority (76%) of households spent less than 3% (sample mean) on organic, and we categorize them as trivial organic users. While for those households with more than 10% expenditure on organic, they are regular organic users, accounting for 8% of the total households. The remaining are referred as occasional organic users. Moreover, the average time between shopping visits is 5.95 days, and it differs substantially across households. Finally, we measure the household coupon usage as the percentage of items purchased with coupons for one household and an average of 8% household purchases are made with coupons.

Format Loyalty Index As discussed in the previous chapter, the exponentially weighted loyalty variable for household i patronizing retail format j at week t takes the form:

$$LOY_{ijt} = \lambda LOY_{ijt-1} + (1-\lambda)\, d_{ijt} \tag{6}$$

where λ is the smoothing parameter, following Guadagni and Little's terminology and $d_{ijt} = 1$ if i visited j in t, and 0 otherwise. As shown in equation (6), the loyalty variables are weighted averages of the past choices, and the variation of the loyalty variables across households reflect preference heterogeneity for particular retail formats. In addition, loyalty variables are updated in each week depending on consumer choices in that week so that household stationary preference change is reflected.

As mentioned above, we use the data in 2013 to initialize the price indexes, and we start the indexes by setting $LOY_{ij1} = 1$ if household i patronizes format j in the first week in 2013, otherwise $LOY_{ij1} = 0$. For the smoothing parameter in the loyalty index, in their original paper, Guadagni and Little (1983) first estimated the model with the loyalty index replaced by ten dummies indicating the previous ten choices made by the household, and they estimated λ via fitting an exponential decay curve to the coefficients of the above dummy variables. Fader, et al. (1992) proposed an iterative method by linear approximating the loyalty index with Taylor expansion. However, most studies have their smoothing parameter conveniently set between 0.7 and 0.9 and make no further attempts to refine the parameter. We follow this to avoid the computationally expensive iteration procedure, and we choose $\lambda = 0.85$ to calculate the loyalty indexes. The estimation results are robust to the specification of λ in the vicinity of 0.85 based on a grid search.

Results and Discussion

To test our model specification, we estimate an alternative model without household shopping behavior and sociodemographic variables, and perform a log likelihood ratio test for model selection. The LR test (test statistic = 386.42, p-value = 0) rejects the null hypothesis that coefficients of shopping behavior and sociodemographic variables are zero. This is in contrast to Staus (2009)'s claim that the influence of sociodemographic variables is small. Further, Guadagni and Little (1983) argued that their loyalty indexes can capture much of the preference heterogeneity across households and numerous studies applying their loyalty indexes did not control for other household characteristics. The test result, however, shows that the loyalty indexes do not fully capture household preference and it is necessary to control for other household characteristics, including household shopping behavior and sociodemographic status when modeling retail format choice. The coefficients estimated from the conditional logit model are reported in Table 3.4 and the marginal effects of the explanatory variables on the probability of patronizing each retail format are reported in Table 3.5. Our model performs well: the predicted probabilities are comparable to the shares of retail format visits shown in Table 3.1, though conventional grocery store is slightly overestimated.

The price indexes have the expected sign. For each retail format, an increase in its price index decreases the probability of patronizing that format and increase the probability of patronizing the alternative formats. However, the estimated price index coefficients slightly miss the conventional 10% significance level. This may be because our price indexes are not able to vary over individuals. By contrast, an increase in the loyal index for one retail format leads to increasing probability of patronage that format. This result highlights the strong effect of household preference captured in the previous purchasing history on household retail format choice.

The household preference for organic food affects the choice of the retail formats. Compared with occasional organic users, trivial users are less likely to choose the organic specialty store whereas regular users are more likely to patronize it, other things being equal. This finding is consistent with organic specialty stores' feature of offering a wide selection of organic food. The organic preference, however, does not have significant effects on consumer choosing conventional grocery. This could be explained by the fact that conventional store is the largest retail format to buy food items for all households regardless of their organic food preference. The discounter's efforts in making organic food more widely accessible and affordable may contribute to regular organic users' preference for discount stores. Also, a nonlinear relationship could exist between organic preference and warehouse club patronage: trivial and regular organic users are less likely to shop in this format than occasional organic users. One unique feature of the warehouse club is that households need to buy a wholesale quantity of products in the store, and we expect this feature is against regular organic users' pursue of freshness and healthfulness embodied in organic food, thus resulting in their less patronage. Further, regular organic users are less likely to purchase in the residual format, which could be explained by their limited assortment of organic food and their store images that are hardly associated with the premium organic food.

This result has direct managerial implication for the retailers in their competition in the organic food sector. Besides increasing the organic offerings in store to cater to consumers' increasing demand for organic foods, retailers also need to pay attention to the retail contexts, which could influence consumer perception about their store format. Also, this result is useful for organic producers, processors, and distributors when they plan the marketing their organic food, particularly produce and dairy products, through different retail formats. Additionally, this result may also suggest that a lack of consumers' understanding regarding the implications of organic food. Since all organic food is produced according to the same USDA standard and certified by National Organic Program, organic consumers should be indifferent where they buy their organic food. Consumer education about organic food and USDA organic programs is needed.

As the average interval between trips increases, households are more likely to patronize conventional grocery stores while less likely to patronize organic specialty grocery stores, warehouse clubs, and the residual format. As discussed above that interval between trips is used to measure the shopping cost one household faces and given the substantially smaller number of the organic specialty store and warehouse club, it is intuitive that households with higher shopping cost tend to reduce their cost by patronizing the more accessible retail format, that is, the conventional grocery store. However, it is surprising to find that longer interval also reduces the likelihood of patronage in the residual format, since it is not as difficult to access as the other two formats.

Among the sociodemographic variables, income has the most significant impacts on each format's patronage probability. Households in the highest income group are more likely to shop in the organic specialty grocery store than other households. And the effect of income on the patronage of the organic specialty store seems to have a threshold. The household income, however, does not substantially affect conventional grocery store patronage. Since the conventional grocery store has roughly 60% of the total store visits and households with various income levels, have more than half of their grocery shopping in this format. Moreover, the higher the income, the more likely to shop in warehouse club and less likely in the discounter or residual format. Finally, the remaining demographic characteristics on organic specialty store patronage is generally consistent with the typical profile of organic users.

Conclusion

In this article, we model households' retail format choice in grocery trips with an extended conditional logit model, and we are mainly interested in the role of households' preference for organic food. We find that compared with occasional organic users, regular organic users are more likely to patronize organic specialty stores and discount stores and less likely in warehouse club and the residual format comprised of a convenience store, dollar store, and drugstore. This finding suggests that organic food is perceived differently in different retail format, possibly due to the store image associated with one format; and consumers' preference for organic food would affect where they do their grocery. Besides, pricing level and loyalty indexes are also important in affecting consumer retail format choice. Though the loyalty indexes proposed in Guadagni and Little (1983) capture a large proportion of individual preference heterogeneity and change, they do not incorporate all household characteristics reflected in household shopping behavior and sociodemographic status, and thus accounting for the impacts of these variables on preference is also important.

A final note concerns the food demand analysis. Given the increasing product differentiation in the food sector and the evolving marketing channel, consumer food demand can be affected by a wider range of factors besides the traditional economic factors and advertising. It is thus important not to ignore the effects of the new factors in the demand analysis.

Tables

Table 3.1 Summary Statistics of Retail Format

Retail format	Org. Specialty Grocery	Conv. Grocery	Discounter	Warehouse Club	Residual
Visits Share (count)	1.8%	59.6%	18.7%	12.2%	7.6%
Retail Chains (count)	13	69	12	6	70
Store (count)	341	2489	526	47	1493
UPC (count)	19631	110868	80108	20760	51945
Food Item (%)	88.5%	77.7%	46.2%	76.6%	41.2%
Organic Share (UPC count)	15.9%	7.7%	4.4%	4.0%	4.2%
Organic Share (Expenditure)	8.2%	2.9%	2.1%	6.1%	3.3%

Table 3.2 Product Modules in Basket

refrigerated yogurt	bottled water
carbonated soft drinks	cookies
low-calorie soft drinks	potato chips
fresh bread	frozen Italian entrees
refrigerated milk	bulk ice cream
canned soup	precut fresh salad mix
fruit drinks	fresh eggs
ready-to-eat cereal	frozen novelties
remaining fresh fruit	frozen pizza
chocolate	pasta

Table 3.3 Descriptive Statistics of the Explanatory Variables

Variables	Definition	Mean (SD)
$org1$	=1 if HH organic expenditure share of produce and dairy products is below 3%, 0 otherwise	0.76 (0.42)
$org2$	=1 if HH organic expenditure share of produce and dairy products is between 3% and 10%, 0 otherwise	0.16 (0.36)
$org3$	=1 if HH organic expenditure share of products and dairy products is above 10%, 0 otherwise	0.08 (0.27)
avg_int	average time interval between grocery trips (days)	5.95 (2.28)
$coupon$	coupon use ratio (%)	0.08 (0.12)
$inc1$	=1 if HH income is below $45000, 0 otherwise	0.25 (0.43)
$inc2$	=1 if HH income is between $45000 and $70000, 0 otherwise	0.23 (0.41)
$inc3$	=1 if HH income is between $70000 and $100000, 0 otherwise	0.26 (0.44)
$inc4$	=1 if HH income is above $100000, 0 otherwise	0.25 (0.43)
$hhsize$	household size (count)	2.45 (1.21)
$age1$	=1 if HH head age is below 40, 0 otherwise	0.05 (0.22)
$age2$	=1 if HH head age is between 40 and 64, 0 otherwise	0.59 (0.49)
$age3$	=1 if HH head age is above 65, 0 otherwise	0.36 (0.48)
$college$	=1 if HH head education is some college or above, 0 otherwise	0.55 (0.5)
$white$	=1 if HH head is white, 0 otherwise	0.73 (0.44)
$single$	=1 if single HH, 0 otherwise	0.13 (0.33)

Note: Number of households in the sample is 1236.

Table 3.4 Conditional Logit Estimation

	Conv. Grocery	Discounter	Warehouse Club	Residual
Alternative Variant Variables				
PI	-0.1010 (0.0693)			
loy	4.0964** (0.0257)			
Alternative Invariant Variables				
$org1$	0.634** (0.0956)	0.6378** (0.1015)	0.5345** (0.1007)	0.7063** (0.1083)
$org3$	-0.1614 (0.1126)	-0.0495 (0.1271)	-0.3047** (0.1252)	-0.6553** (0.1654)
avg_int	0.0811** (0.02)	0.0596** (0.0208)	0.0304 ǂ (0.021)	0.031 (0.0222)
$coupon$	-0.4071 (0.3666)	-0.0477 (0.3847)	0.2118 (0.393)	0.57 (0.4118)
$inc2$	-0.1713 (0.1318)	-0.2858** (0.1356)	-0.0933 (0.14)	-0.2773** (0.1405)
$inc3$	-0.1659 (0.1242)	-0.1745 (0.1284)	-0.0456 (0.1318)	-0.3308** (0.1345)
$inc4$	-0.5424** (0.1285)	-0.6187** (0.1338)	-0.3594** (0.1367)	-0.8012** (0.1413)
$hhsize$	0.1657** (0.0435)	0.1803** (0.0446)	0.1647** (0.0451)	0.1473** (0.0465)
$age2$	-0.131 (0.1446)	-0.1657 (0.1524)	-0.0889 (0.1595)	0.0661 (0.1776)
$age3$	-0.2301 (0.1583)	-0.2613 ǂ (0.1659)	-0.1069 (0.1729)	0.0316 (0.1909)
$college$	-0.1554* (0.0924)	-0.2522** (0.0955)	-0.1953** (0.0972)	-0.1875* (0.1008)
$white$	0.0769 (0.0901)	0.0778 (0.0937)	0.1636* (0.0948)	0.0755 (0.0997)
$single$	0.0128 (0.132)	-0.005 (0.1374)	-0.121 (0.1449)	-0.0463 (0.145)
$const$	-0.0214 (0.2747)	0.4492 ǂ (0.2853)	0.3617 (0.293)	0.1693 (0.3101)
Likelihood	-33976.942			
N	248615			

Note: Standard errors in parentheses. ** and * indicate significant at 5% and 10%, respectively.

Table 3.5 Marginal Effects Estimates

	Org. Specialty Grocery	Conventional Grocery	Discounter	Warehouse Club	Residual
Probability	0.0150	0.702	0.1344	0.0930	0.0557
PI_1	-0.0015 (0.001)	0.0011 (0.0007)	0.0002 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)
PI_2	0.0011 (0.0007)	-0.0211 (0.0145)	0.0095 (0.0065)	0.0066 (0.0045)	0.0039 (0.0027)
PI_3	0.0002 (0.0001)	0.0095 (0.0065)	-0.0117 (0.0081)	0.0013 (0.0009)	0.0008 (0.0005)
PI_4	0.0001 (0.0001)	0.0066 (0.0045)	0.0013 (0.0009)	-0.0085 (0.0058)	0.0005 (0.0004)
PI_5	0.0001 (0.0001)	0.0039 (0.0027)	0.0008 (0.0005)	0.0005 (0.0004)	-0.0053 (0.0036)
LOY_1	0.0605** (0.0028)	-0.0431** (0.002)	-0.0083** (0.0004)	-0.0057** (0.0003)	-0.0034** (0.0002)
LOY_2	-0.0431** (0.002)	0.8571** (0.006)	-0.3866** (0.0048)	-0.2673** (0.0042)	-0.1601** (0.0033)
LOY_3	-0.0083** (0.0004)	-0.3866** (0.0048)	0.4767** (0.0059)	-0.0512** (0.0011)	-0.0307** (0.0008)
LOY_4	-0.0057** (0.0003)	-0.2673** (0.0042)	-0.0512** (0.0011)	0.3454** (0.0053)	-0.0212** (0.0006)
LOY_5	-0.0034** (0.0002)	-0.1601** (0.0033)	-0.0307** (0.0008)	-0.0212** (0.0006)	0.2153** (0.0044)
$org1$	-0.0093** (0.0013)	0.01 (0.0074)	0.0024 (0.0054)	-0.0079** (0.0038)	0.0048 (0.0031)
$org3$	0.0028* (0.0016)	0.0164 (0.0123)	0.0182** (0.0089)	-0.0112* (0.0062)	-0.0262** (0.0067)
avg_int	-0.001** (0.0003)	0.0082** (0.0013)	-0.0013 (0.0009)	-0.0036** (0.0007)	-0.0021** (0.0006)
$coupon$	0.0036 (0.0054)	-0.1168** (0.0233)	0.026 (0.017)	0.0421** (0.0143)	0.0451** (0.0107)
$inc2$	0.0027 (0.0019)	0.0081 (0.0077)	-0.0139** (0.0052)	0.0083* (0.0048)	-0.0053* (0.003)
$inc3$	0.0024 (0.0018)	-0.0023 (0.0077)	-0.0016 (0.0053)	0.0109** (0.0046)	-0.0094** (0.0031)
$inc4$	0.0081** (0.0019)	-0.0003 (0.0084)	-0.0103** (0.0059)	0.017** (0.0048)	-0.0144** (0.0035)

(Continued)

Table 3.5 Continued

	Org. Specialty Grocery	Conventional Grocery	Discounter	Warehouse Club	Residual
$hhsize$	-0.0025**	0.0011	0.0022	0.0001	-0.0009
	(0.0006)	(0.0024)	(0.0017)	(0.0014)	(0.001)
$age2$	0.0018	-0.0085	-0.0063	0.0028	0.0103*
	(0.0021)	(0.0118)	(0.0079)	(0.0069)	(0.0058)
$age3$	0.0031	-0.0177	-0.0076	0.0091	0.0132**
	(0.0023)	(0.0125)	(0.0083)	(0.0072)	(0.006)
$college$	0.0026*	0.0114**	-0.0108**	-0.0022	-0.0009
	(0.0013)	(0.0057)	(0.004)	(0.0032)	(0.0024)
$white$	-0.0013	-0.0049	-0.0008	0.0074**	-0.0005
	(0.0013)	(0.0061)	(0.0043)	(0.0035)	(0.0026)
$single$	0.0001	0.0129	0.0001	-0.0107*	-0.0023
	(0.0019)	(0.0093)	(0.0063)	(0.006)	(0.0037)

Note: Standard errors in parentheses. ** and * indicate significant at 5% and 10%, respectively.

Figures

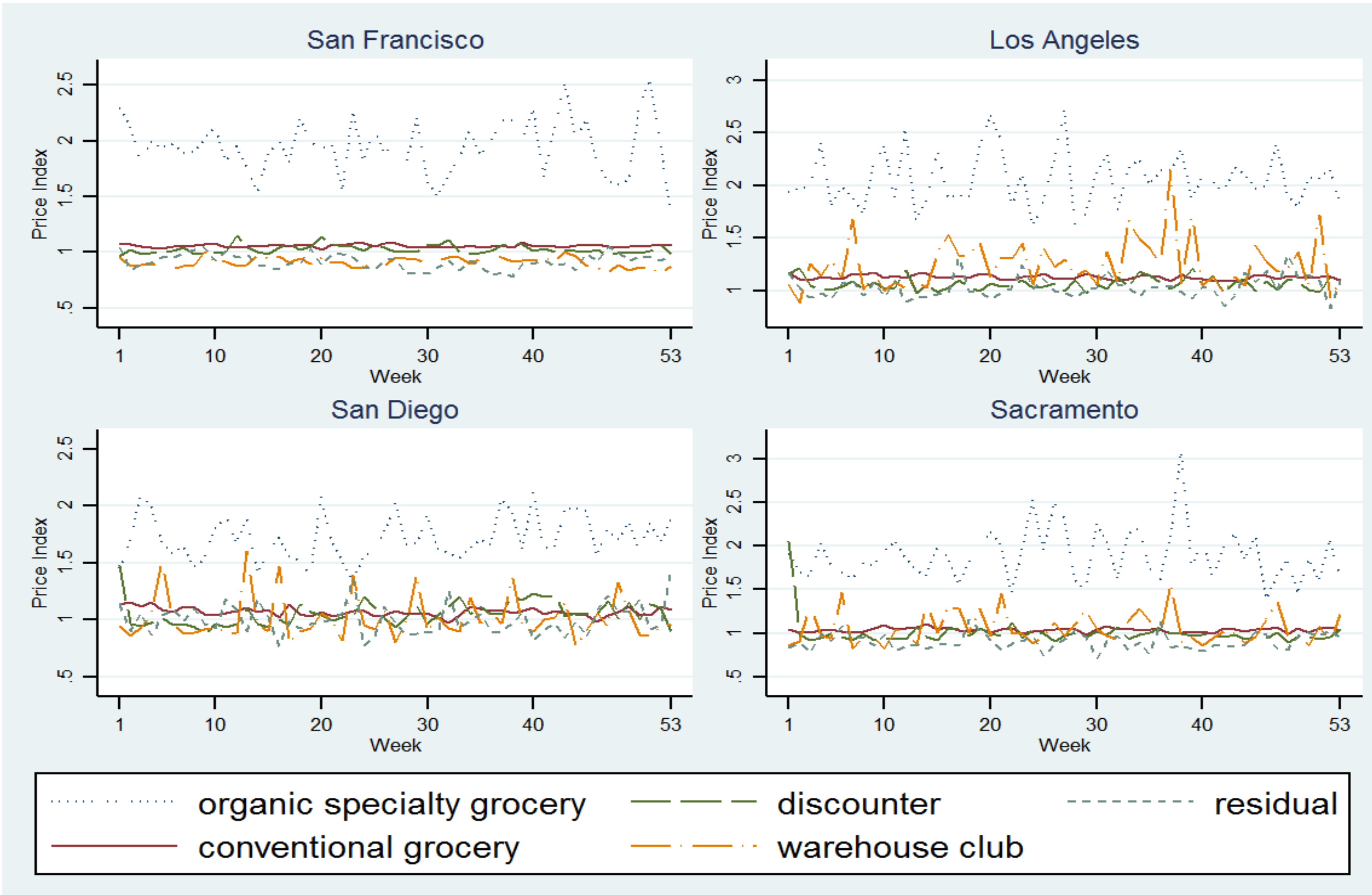

Figure 3.1 Price Index in Main Scantrack Market in California

Chapter 4 Relation between U.S. Farmers' Adoption of Organic Farming and Direct Marketing

Introduction

The markets for organic food and local food[6] have been experiencing substantial growth over recent years in the U.S. The total organic sale has reached a record level of 43.3 billion dollars in 2015, an 11-percent increase from the previous year (Organic Trade Association, 2016). A similar trend can be identified for the total sale of foods marketed through direct marketing channels, which reaches 8.7 billion dollars in 2015 (USDA, 2015). The high demand for organic and local food and the price premium they command encourage farmers to adopt organic farming and direct marketing practices. As of 2014, the number of farms adopting organic farming reached 14,093, covering a total land area of 3.67 million acres, and in 2015, 167 thousand farms reported that they adopted some direct marketing practices (USDA, 2015).

Organic food and local food address consumers' increasing concerns about food nutrition, safety, and environmental degradation of the conventional agricultural system, and this attributed to their strong growth (Hughner, et al., 2007; Martinez, et al., 2010; Nasir and Karakaya, 2014). Moreover, promoting organic farming and promoting direct marketing have gradually evolved as important rural development initiatives (Bagi and Reeder, 2012). By encouraging farmers to grow organic foods and sell them on the local market, it is believed that more food dollars can be kept in the local economy, thus benefiting farmers and consumer alike. Also, organic farming prevents the use of certain

[6] Although there is no consensus on the definition of local foods, definitions based on market arrangement, including direct-to-consumer sales and direct-to-retail/foodservice sales, are well recognized (Martinez, et al., 2010). Thus we define local foods as those sold through direct marketing channels. For a more comprehensive discussion of the definition of local food, please refer to Hand and Martinez (2010).

synthesized fertilizers and pesticides, while direct marketing reduces food supply chains and reduces food miles as well. Both have potential environmental benefits.

These features of organic farming and direct marketing provide justifications for policies aiming to promote these two practices among farmers, and the policies play a major role in the development of organic and local food systems. As early as 2002, the National Organic Program (NOP) was established to regulate organic product certification and labeling at the federal level, which is essential for the organic market due to the credence attribute nature of organic food. Moreover, the financial assistance for organic certification and funding for organic research has steadily increased over each of the last three Farm Bills, reaching 57.5 and 100 million dollars respectively in the 2014 Act (USDA, 2016). It needs to be noted, however, that unlike their European counterparts, farmers are not directly subsidized to adopt organic farming in the U.S. (Lohr and Salomonsson, 2000). The promotion of local food production and marketing is incentivized by numerous programs at the federal and state levels. Notably, USDA's Know Your Farmer, Know Your Food (KYF2)[7] provides loans and grants to support each step in the local and regional food supply chain. Also, USDA and other federal agencies provide local and regional production advice and guidance. At the state level, each state has its state-sponsored agricultural marketing program (e.g. Kentucky Proud in Kentucky and California Grown in California). Though these programs vary in program components, they all aim to capture the local food consumers (Onken and Bernard, 2010).

[7] For more information about this program, please refer to https://www.usda.gov/wps/portal/usda/knowyourfarmer?navid=kyf-resources-report.

From a policy perspective, an understanding of what factors affect the adoption of organic farming or direct marketing is critical in making effective policies in promoting either practice. However, given their overall similarities regarding satisfying consumer needs, increasing farm income, and meeting government's rural development objective, there seems to be a gap in understanding the relation between the adoption of the two practices among U.S. farmers. A deeper understanding of this relationship could be invaluable in coordinating existing policies and programs in promoting the two practices. We fill the gap by examining this relationship utilizing farm level data from USDA's Agricultural and Resource Management Survey. We further evaluate the effects of both practices on gross farm income.

The remainder of the article is organized as follows. Section 2 reviews literature on adoption of organic farming and direct marketing and introduces the central research question and objectives. Section 3 discuss the econometrics methodology, and section 4 describes the data. Section 5 presents the results and discusses some policy implications. Section 6 concludes.

Literature Review

Organic farming and direct marketing have drawn substantial research interests in recent years. The literature mainly focuses on two topics: 1) identifying factors affecting farmers' adoption of either practice and 2) evaluating the effects of the two practices on farm income. The two issues have direct implications for policymakers and farmers alike. We briefly review studies on these two items, based on which we further introduce our research question and primary objectives.

Organic Farming Adoption

Numerous factors have been shown to affect farmers' adoption of organic farming. Though the demographic profile of organic farmers varies across farm type, location and time under study, they tend to be younger, have less farming experience, and are more educated than non-organic farmers (Bagi and Reeder, 2012; Burton, et al., 1999; Genius, et al., 2006; Kallas, et al., 2010). Additionally, female farmers are also more likely to adopt organic farming (Bagi and Reeder, 2012; Burton, et al., 1999). While the mechanisms through which sociodemographic characteristics affect organic farming adoption remain unclear, some studies suggest that sociodemographic characteristics can affect farmers' information acquisition (Genius, et al., 2006), adoption motivation (Peterson, et al., 2012), and risk perception (Bagi and Reeder, 2012), all of which play important roles in organic farming adoption.

In their study of organic land conversion in Crete, Greece, Genius, et al. (2006) found that farmers make joint decisions of information acquisitions and organic land conversions. A trivariate ordered probit model is used to evaluate whether farmers' decision to gather information, either actively or passively, increases their probability of organic conversion. Besides the conventional information sources, Lewis, et al. (2011) postulate that farmers may gather information about organic farming from their neighbors, which could reduce the uncertainty of organic farming adoption and lower the cost of learning. They provide evidence in their study of organic farming adoption among dairy farms in Wisconsin with spatial econometrics techniques.

Moreover, in their duration analysis of vineyard farmers' organic practice adoption in Catalonia, Spain, Kallas, et al. (2010) found that farmers who are willing to preserve the environment and generate employment in the local area are more likely to convert to organic farming in a shorter period. The same can be said for farmers who have positive attitudes and opinions towards organic farming. They also found risk-loving farmers are more prone to adopt. With a similar duration analysis technique, Läpple (2010) studied Irish stock farmers organic farming adoption. Their main findings are also similar: Farmers who express environmental concerns are more likely to adopt and less likely to abandon organic farming. Additionally, risk-averse farmers are less likely to adopt.

Among farm characteristics under study, farm size receives the most scrutiny in the literature. However, its impact on the organic farming adoption decision is mixed. While some studies found evidence that small farms are more likely to convert to organic (Bagi and Reeder, 2012; Burton, et al., 1999; Kallas, et al., 2010), others failed to find significant effects (Genius, et al., 2006).

Economic factors, including organic price premium, availability of subsidy, and conversion costs are also important in making adoption decisions, despite that farmers could have multiple motivations to adopt organic farming besides profit maximization. It is established that a high organic price premium and subsidy to organic farmers encourage farmers to adopt organic farming whereas high conversion costs discourage adoption (Latruffe and Nauges, 2014; Lohr and Salomonsson, 2000; Serra, et al., 2008).

Direct Marketing Adoption

In contrast to the global interests in organic farming adoption, research on direct marketing adoption are relatively scarce and primarily concentrated in the U.S. Early studies mainly focus on the effects of farm and farmer characteristics on sales from direct marketing. Importantly, the geographical closeness to urban areas is found to increase direct marketing sales (Brown, et al., 2006; Brown, et al., 2007; Govindasamy, et al., 1999). This is intuitive since cities have significant demands for products sold via direct marketing, and prices also tend to be higher in cities. One major drawback of these studies, however, is that all observations in their data are direct marketers, which makes it impossible to understand what factors drive farmers' adoption of direct marketing.

Monson, et al. (2008) is the first to fill the gap by modeling small fruit and specialty product farmers' choice of direct marketing practice with an ordered logit model. They found that large farms are less likely to adopt direct marketing; this might be because it is more economical for large farms to choose buyers that can absorb a greater share of their production. By contrast, farmers producing high-value crops are more likely to adopt direct marketing since high-value producers are more incentivized to capture a larger proportion of the total value of their products. Interestingly, farmers implementing organic production without USDA organic certification are more likely to adopt direct marketing. They argued that consumers preferring organic foods may not rely on USDA certification but rather trust local farmers' organic claims, and this leaves organic farmers without USDA certification to choose to sell their products directly to consumers.

Recently, as richer datasets from Agricultural Resource Management Survey (ARMS) become available, several studies shed more light on farmers' adoption of direct marketing practice and its effect on gross farm income or sales from direct marketing. Detre, et al. (2011) used a double hurdle model to evaluate the effects of farm and farmer characteristics on direct marketing adoption and income from it. They confirmed the importance of these factor in determining farmers' choice and revenue from direct marketing. Closeness to metropolitan areas and adoption of organic practices increase farmers' likelihood of adopting direct farming and revenue from direct marketing. Uematsu and Mishra (2011) took a different modeling approach and found farm and farmer characteristics affect the intensity of direct marketing adoption, but direct marketing adoption does not have significant effects on gross farm income.

Relation Between Organic Farming and Direct Marketing

In the current literature, farmers' adoption of organic farming/direct marketing is studied in isolation from the adoption of direct marketing/organic farming. It is important to recognize, however, that these two decisions need not be independent of each other, and farmers may jointly consider the adoption of the two practices. On the one hand, the adoption of one method may increase the probability of adopting the other. First, the incentives for adopting the two practices are considerably overlapping for farmers. For example, both organic farming and direct marketing are proposed to protect the environment and reduce adverse effects of farming on the environment. Numerous farmer sociodemographic and farm characteristics are shown to have the same qualitative effects on farmers' adoption of the two practices. Also, some consumer demand studies suggest that the organic attribute of a food tends to be complementary to the local attribute (Connolly and Klaiber, 2014; Gracia, et al., 2014). This complementary relation between organic and local attribute may encourage farmers to adopt organic farming and direct marketing at the same time.

On the other hand, the adoption of one practice may reduce the probability of adopting the other. First, unlike the first organic farms, organic farms nowadays tend to rely on a portfolio of marketing channels. As the demand for organic foods grows, it is expected that organic farms concentrated on the west coast and northeast region would employ intermediate channels to distribute their organic foods. Thus organic foods need not be local foods sold through direct marketing channels. Importantly, the income of farmers who commit to local direct selling is significantly lower than farmers who employ multiple channels (Park, et al., 2014; Park and Lohr, 2010), and organic farmers may be incentivized to move away from direct marketing channels. Second, although the organic and local attribute are largely complementary in the consumer studies, Connolly and Klaiber (2014) noted this result differs by state; in addition, Gracia, et al. (2014) cautioned about consumer heterogeneity: in their study for a large segment of consumers, the complementary relation holds, yet for a small segment of consumers, the two attributes actually substitute each other. Furthermore, with the rapid development of local food systems and the overlapping implications of local and organic foods, there seems to be a trend of "local is the new organic." Farms which primarily rely on direct marketing report substantially lower production under organic certification (Veldstra, et al., 2014).

In summary, the relation between farmers adoption of organic farming and direct marketing remains an empirical issue. The major objective of this article is to examine this relationship with data from ARMS. We contribute to the understanding of this possible relationship so that policies aiming to promote these two practices can be better coordinated. Our second objective is to reevaluate the effects of either practice on gross farmers' income, based on modeling of the two adoption decisions. The answer to this question sheds light on the profitability of the two practices on U.S. farms.

Model

Given that U.S. farmers marginally adopt organic farming and direct marketing practices, we ignore adoption intensity and model farmers' adoption of either practice as binary choices. Thus, binary choice models, including probit, logit, and linear probability models are the natural options. Since we also expect that the two decisions affect each other and we are interested in jointly modeling the two decisions, a simultaneous bivariate binary choice model serves our purpose. If we choose probit to model each decision, for instance, the model can be specified such that

$$\begin{gathered} Org^{*} = \boldsymbol{X_1} b_1 + \gamma_1 DM + u \\ DM^{*} = \boldsymbol{X_2} b_2 + \gamma_2 Org + v, \\ Org = 1\ if\ Org^{*} > 0, 0\ otherwise \\ DM = 1\ if\ DM^{*} > 0, 0\ otherwise \end{gathered} \tag{1}$$

where Org and DM are dummy variables indicating farmers' adoption of organic farming and direct marketing, respectively. $\boldsymbol{X_1}$ and $\boldsymbol{X_2}$ are vectors of explanatory variables accounting for these two adoption decisions and they share some common variables. Also, the two residual terms u and v are assumed to follow standard bivariate normal distribution.

However, it is believed that simultaneous models involving limited dependent variables as in model (1) are logically inconsistent with non-unique reduced forms and they are thus not identified (Maddala, 1983). A conventional way to circumvent this issue is to make model (1) recursive by restricting either γ_1 or γ_2 equal to 0. In doing so, it implies that one decision is determined exogenously from the other decision, making it impossible to evaluate the effects of one practice on the other.

A potential solution is to follow Jovanovic (1989) and Butler and Mitchell (1990) who note the distinction between non-unique reduced forms and non-unique structure and argue that as long as the structure of a model is unique, it can be identified, even though there could exist multiple reduced forms. Butler and Picone (1999) further prove that model (1) is identified by showing different structures lead to different distributions of the outcomes of the endogenous variables. Based on this result, they propose to estimate the model in (1) directly with GMM, and the orthogonality conditions they use:

$$\begin{aligned} &E[\boldsymbol{X}(Org - \boldsymbol{\Phi}(\boldsymbol{X_1}b_1 + \gamma_2 DM))] = 0 \\ &E[\boldsymbol{X}(DM - \boldsymbol{\Phi}(\boldsymbol{X_2}b_2 + \gamma_1 Org))] = 0, \end{aligned} \tag{2}$$

where $\boldsymbol{X}$ is the union set of $\boldsymbol{X_1}$ and $\boldsymbol{X_2}$ and identification is achieved via excluded instrumental variable in each equation.

We follow this estimation strategy. However, the simultaneous bivariate probit model outlined above fails to converge. To overcome this difficulty, we employ linear probability models to model each adoption decision while also accounting for the joint adoptions. This yields a simultaneous bivariate linear probability model such that:

$$\begin{aligned} Org &= \boldsymbol{X_1}b_1 + \gamma_1 DM + u \\ DM &= \boldsymbol{X_2}b_2 + \gamma_2 Org + v, \end{aligned} \tag{3}$$

where all the notations have their original meanings. We still use GMM to estimate equation (3), and we maintain the same sets of instrumental variables for each equation. The orthogonality conditions accordingly change to

$$\begin{aligned} &E[\boldsymbol{X}(Org - \boldsymbol{X_1}b_1 - \gamma_1 DM)] = 0 \\ &E[\boldsymbol{X}(DM - \boldsymbol{X_2}b_2 - \gamma_2 Org)] = 0. \end{aligned} \tag{4}$$

The use of linear probability model (LPM) in modeling binary choices is debatable in the econometrics literature. We do not aim to offer a thorough discussion of the linear probability model; however, we acknowledge some shortcomings of the model documented in the literature, mainly heteroscedastic residuals and predicted probabilities outside the unit interval (Greene, 2012). The heteroscedastic residual can be addressed using heteroscedasticity-robust standard errors, and the LPM can approximate true probabilities and give good estimates of marginal effects of explanatory variables on response probabilities over a range of explanatory variables (Angrist and Pischke, 2008; Wooldridge, 2010).

The second objective of this paper is to evaluate the effects of the two practices on gross farm income. This could be achieved by regressing farm income on the adoption of the two practices and other factors affecting farm income, such that

$$y = \beta_1 Org + \beta_2 DM + \boldsymbol{X_3} b_3 + \varepsilon. \quad (5)$$

A direct estimation of equation (5) with OLS could generate inconsistent and biased estimation for β_1 and β_2 since adoption of either practice is unlikely to be randomly assigned among farmers. Common unobservable variables affecting the adoption of either practice and the farm income, when uncontrolled for, are left in the residuals terms, causing ε to be correlated with u or v. This further leads to correlation between ε and the adoption dummy variables, causing these variables to be endogenous in equation (5). To address the endogeneity issue, we replace the adoption dummies in equation (5) with the predicted probabilities of adoption of either practice and continue to estimate the equation with OLS. In addition, robust standard errors are calculated for inferences.

Data

The main data source is a dataset from the 2012 ARMS, conducted jointly by USDA's Economic Research Service (ERS) and National Agricultural Statistics Services (NASS). With a multiphase, multi-frame, and stratified survey design, the ARMS provides detailed information regarding the financial conditions, production practices, marketing practices, farm characteristics, and operator characteristics of farm businesses in the 48 U.S. contiguous states on a yearly basis. We further supplement the ARMS with data from the 2012 Census of Agriculture. The census data contains information about the agricultural and rural economy on the county level, and the variables we use are the county-level numbers of farms adopting organic farming and direct marketing, and the number of farmers' market in a county.

The 2012 ARMS data offers a unique opportunity to study the possible joint adoption of organic farming and direct marketing on U.S. farms since both practices were queried in the survey. For organic farming, farm operators indicate whether their operations produce organic products according to USDA's National Organic Program (NOP) standards or have acres transitioning into USDA NOP production. However, given the low organic farming adoption rate, we do not further differentiate organic operations by their USDA certification status[8]. For direct marketing, two questions are relevant: Operators indicate whether they sell their products directly to individual consumers, including sales from roadside stands, farmers markets, pick you own, door to

[8] In the ARMS data, there are four types of organic production: certified production, production exempt from certification, production transitioning to certification, and production according to USDA NOP standards but not certified or exempt. The latter two types cannot be sold as organic and thus they do not command an organic premium, which could bias downward the estimation of the effect of organic production on gross farm income. However, due to their small sizes, the bias should be minimal.

door, and Community Supported Agriculture (CSA). Also, operators indicate whether they sell products directly to retail outlets, including restaurants, grocery stores, schools, hospitals, or other businesses. We combine both types of marketing channels into a broader definition of direct marketing. Also, we only include family farms which are not run by hired managers in our analysis. After dropping observations with key explanatory variables missing, the sample size is 14960.

As shown in Table 4.1, organic farming and direct marketing are not widely adopted among U.S. family farms, with the adoption percentage of 1.84% and 7.17% respectively, and even fewer farmers choose to adopt both practices. The Pearson and Tetrachoric correlation coefficients suggest that the two adoption decisions could be positively correlated. Further, the gross farm income of organic farmers is significantly higher than that of non-organic farms whereas the income difference is not significant between farms adopting direct marketing and those do not.

Table 4.2 presents the explanatory variables, most of which are dummy variables describing farm characteristics, farm operator sociodemographic status, and practices on farms. We choose these variables based on studies we review above and the data availability in the ARMS.

Variables used to explain the adoption of both practices include farm type and size, a region where the farm is located, diversification index, use of marketing contract and production contract, principal operator’s age, gender, education, main occupation, and time spent working off farms. Since our sample covers the entire agricultural sector in the U.S., and the adoption of organic farming and direct marketing varies substantially across farm type, farm size, and farm region, it is important to control for these factors.

Specifically, high-value crops, including fruits and vegetables, are the largest food category in the organic sector, and thus farmers producing high-value crops are more likely to adopt organic farming. By contrast, the logistic requirements of direct marketing may inhibit large commercial farms from adopting direct marketing since they are not able to exploit economies of scale. Since organic and local foods are well received in the west coast and northeastern regions, it is expected that farms in these areas are more likely to adopt the two practices. High-value crops and dairy farms, closely associated with organic farming or direct marketing, represent 11.3% and 6.5% of all farms, respectively. Large commercial farms represent 44% of all farms.

Moreover, the use of marketing or production contracts could free farmers from selling their produce, thus reducing the likelihood of adopting direct marketing. As discussed above, farmers' attitudes and perceptions towards the two practices can affect their adoption decisions; we use farmers' sociodemographic characteristics to proxy for these attitudes and perceptions. The profile of a typical farm operator is 58 years old male with at least a high school education. 71% of principal operators report farming is their main occupation, and 41% report they spent time working off farms.

Besides these common explanatory variables in both equations, we include whether the farm has internet access and the number of organic farms in the county where the farm is located to explain farm adoption of organic practice. The internet access on the farm would affect farmer's information acquisition, which has already been documented to increase farm's adoption. Farm's adoption could be encouraged by their peer farms decisions to adopt organic farming, and we use the number of organic farms in the county where a farm is located to measure this peer effect. Note that these two variables are not likely to affect farmers' adoption of direct marketing, and we also use them to instrument for the organic adoption variable in the direct marketing adoption equation. Additionally, we use three variables to explain farm' adoption of direct marketing: distance from farm to the nearest major town/city, the number of farms adopting direct marketing and number of the farmers market in the county where the farm is located. Previous studies have emphasized the importance of farm location in farmer's decision to adopt direct marketing. It is expected the closer the farm is to urban areas, the more likely are farmers to adopt direct marketing. A peer effect could also exist for direct marketing adoption, and we measure this effect with a similar count of farms adopting direct marketing on a county level. Farmer's market is one major avenue in direct marketing, and it is expected that it has a positive effect on farmers' direct marketing adoption. Because these variables do not tend to affect farmers' adoption of organic farming, we thus use these variables to instrument for the direct marketing adoption variable in the organic farming adoption equation.

Finally, in the gross farm income equation, in addition to the common explanatory variables, we substitute the adoption variables with the predicted probability of the adoption to evaluate the effects of farmers' adoption of organic farming and direct marketing on gross farm income. Moreover, we also control for farm input, including total acres and hired labor hours on farms, and whether farm receives a government payment.

Results and Discussion

Table 4.3 presents the estimation results of organic farming and direct marketing adoption equations, and Table 4.4 presents the estimation result of gross farm income equation. The models perform satisfactorily, and the instruments used in the two adoption equations pass the over-identification tests.

Adoption of Organic Farming and Direct Marketing

Compared with other crop farms, cash grain farms are less likely to adopt either organic farming or direct marketing whereas high-value crop farms are more likely to adopt both practices. By contrast, dairy farms are less likely to choose direct marketing and more likely to adopt organic farming while the reverse can be said about other animal farms. These distinctions reflect the characteristics of different farming enterprises. Fruits, vegetables, and dairy products are the most common organic products on the market, and farms producing these products are more likely to adopt organic farming. Cash grains and dairy products need further processing, which explains that farms producing them are less likely to adopt direct marketing. While farm size does not have a significant effect on organic farming adoption, it negatively affects direct marketing adoption. This result is also expected since larger farms tend to rely on marketing contracts to sell a lot of products, and thus they are less likely to resort to direct marketing, which could substantially increase marketing cost. Further, the adoption of either practice shows similar regional patterns. Compared with the Heartland region, the Northern Crescent region in the northeast and the Basin and Range in the west of the U.S. are more likely to adopt either practice. This is consistent with the factor that organic food and local food are popular in these regions.

Additionally, farmers' sociodemographic characteristics also have similar effects on farmers' adoption of either practice. Young and female farmers are more likely to adopt both practices. The effect of education on adoption, however, seems to be nonlinear. Farmers’ probability of choosing either method decrease first and then increases as the education level increases. As discussed above, sociodemographic status, including education, a proxy for farmers’ attitudes and perceptions towards the two practices, and the nonlinearity might suggest heterogeneous motivation in adopting these practices.

The diversity of farm enterprises is shown to have a positive impact on the adoption of both practices. The use of production contract or marketing contract has little effects on the probability of organic farming adoption. However, they tend to decrease the probability of direct marketing adoption, especially for marketing contracts. This is understandable since the use of marketing contracts makes it unnecessary for farmers to engage in direct marketing.

The effects of many variables discussed so far on adoption of either practice are qualitatively identical, and this contributes to the positive correlation between adoption of the two practices, indicating farmers’ simultaneous adoption of the two practices. However, after controlling for these variables, farmers’ adoption of organic farming reduces the probability of adopting direct marketing, and direct marketing adoption reduces the chance of organic farming adoption, though the latter effect is small and insignificant, suggesting the substitution between the two practices. This may be contributed by limited local demand. To exploit the economies of scale and offset the high cost of organic farming, many organic farms expand their operations, causing the supply to exceed the demand that can be met through local direct marketing channels. The local glut then propels farmers to sell to intermediaries with various marketing contracts and forgo direct marketing. Gross organic farm income, which is roughly three times that of the non-organic farms as shown in Table 4.1, provides some supports for this explanation. Another possible explanation concerns the high cost of direct marketing. For small farms, it might be economical to sell locally through direct marketing channels while for large organic farms, it would be costly to find direct marketing channels for a lot of organic goods. This could drive those large organic farms to wholesalers and other intermediaries to lower their per-unit marketing costs. Given the finding, we tentatively suggest that policies towards promoting organic farming be more focused on small farms since they can meet small local demand by employing various direct marketing channels. Additionally, programs supporting direct marketing could also integrate an organic component, helping farmers to adopt organic farming and market their organic products via direct marketing channels.

Lastly, access to the internet, to our surprise, has a negative yet not significant effect on organic farming adoption. This could suggest that the internet might not be farmers' main venues to acquire information regarding organic farming. As expected, there exist peer effects in farmers' organic farming adoption. And a similar peer effect can also be found for direct marketing. The distance to major city/town from farms has a negative effect on the probability of farmer's direct marketing adoption. Finally, the more farmers markets in a county, the more likely farmers adopt direct marketing. This result can suggest that farmers market may be substantial among all direct marketing channels.

Effects of Organic Farming and Direct Marketing on Farm Income

Table 4.4 shows the estimation results of gross farm income. Most of the variables included in the model have expected significant impacts on the gross farm income. Notably, the income of farms adopting organic farming is 2.16% higher than those who do not, other things being equal. The adoption of direct marketing has a slightly negative yet insignificant impact on gross farm income. This result is in contrast to Uematsu and Mishra (2012) in which no significant effect on farm income is found for USDA NOP certified organic production in 2008. This change may well reflect the transition the U.S. organic industry is going through in recent years. The small-scale farming typically associated with organic farming might not be able to meet consumer's growing demand for organic food, which could motivate many organic farmers to expand their production and sell large quantities of organic products at a premium. The adverse effect of direct marketing on farm income, however, is consistent with previous findings as in Park, et al. (2014) and Park and Lohr (2010).

Moreover, farm income varies across farm type, size, and regions. This is expected given the heterogeneity of the U.S. farming businesses. The sociodemographic status of the operators and the practice on farms also play important roles in explaining farm income. In particular, age has a slightly negative impact on farming while the more educated the operators, the higher the farm income. Additionally, operator's primary occupation is farming has a positive impact on farm income whereas operator's time spent working off farms has an adverse impact on farm income. These results highlight the importance of developing farming professionalism in the agricultural sector.

Furthermore, the more diversified the farm, the higher farm income. This may be contributed by diversified farms capabilities to cope with production or marketing risks. Furthermore, having a production contract has a negative effect on farm income whereas having a marketing contract has a positive effect on farm income. And the more input usage, labor, and land, the higher the farm income. Finally, government payment also increases farm income.

Conclusion

Organic farming and direct marketing are gaining momentum in the U.S. due to consumer's growing demand for organic food and local food and also due to government policies and programs promoting the two practices since they are considered to be important rural development strategies. This study investigates the relation between farmers' adoption of organic farming and direct marketing practices and evaluates their effects on gross farm income. The main finding is that farm's adoption organic farming reduces the probability of adopting direct marketing while the direct marketing adoption does not have a significant effect on organic adoption. Also, organic farming adoption is found to increase gross farm income while no significant effect can be found for direct marketing adoption. We recommend that organic farming policies need to focus more on small farms and programs promoting direct marketing incorporate components to help farmers adopt organic farming.

We only evaluate the effects of the two practices on gross farm income. It needs to be noted that organic farming's environmental and health benefits are hard to quantify. Though we fail to find a significant effect of direct marketing on farm income, its impact on general rural development cannot be ignored. Further research may need to evaluate the effects of policies promoting organic farming and direct marketing more thoroughly.

Tables

Table 4.1 Descriptive Statistics of Practice Adoption and Gross Farm Income

	Non-Direct Marketing	Direct Marketing	Total
Non-organic	13706	978	14684 (98.16%)
Organic	181	95	276 (1.84%)
Total	13887 (92.83%)	1073 (7.17%)	14960

Pearson correlation coefficient: 0.145, p-value 0.00
Tetrachoric correlation coefficient: 0.4492, p-value 0.00

	Gross Farm Income	T-statistic (p-value)
Non-organic	703414	-10.4177 (0.00)
Organic	2239951	
Non-Direct Marketing	730512.1	-0.2257 (0.82)
Direct Makreting	747936.6	

Table 4.2 Descriptive Statistics of the Explanatory Variables

Variables	Description	Mean (Std. Err.)
cgrain	= 1 if the largest proportion of the farm total gross value of sale comes from cash grain, 0 otherwise	0.384 (0.486)
hvc	= 1 if the largest proportion of the farm total gross value of sale comes from high value crops, 0 otherwise	0.113 (0.316)
mdairy	= 1 if the largest proportion of the farm total gross value of sale comes from dairy products, 0 otherwise	0.065 (0.246)
oanimal	= 1 if the largest proportion of the farm total gross value of sale comes from other animal products, 0 otherwise	0.365 (0.481)
intermediate	= 1 if the farm is an intermediate farm, 0 otherwise	0.298 (0.457)
commercial	= 1 if the farm is a commercial farm, 0 otherwise	0.44 (0.496)
age	principal operator age	58.312 (12.548)
male	= 1 if principal operate is male, 0 otherwise	0.943 (0.233)
edu2	= 1 if completed high school	0.377 (0.485)
edu3	= 1 if have some college	0.298 (0.457)
edu4	= 1 if completed college or above	0.27 (0.444)
occ_farming	= 1 if principal operator's main occupation is farming	0.714 (0.452)
offwork	= 1 if principal operator report working time off the farm, 0 otherwise	0.416 (0.493)
entropy	Farm diversification index	0.164 (0.142)
prd_contract	=1 if the farm has production contract for any commodity produced	0.077 (0.267)
mkt_contract	=1 if the farm has marketing contract for any commodity produced	0.216 (0.412)
region2	=1 if the farm is located in the Northern Crescent region, 0 otherwise	0.126 (0.331)
region3	=1 if the farm is located in the Northern Great Plains region, 0 otherwise	0.041 (0.197)

(Continued)

Table 4.2 Continued

Variables	Description	Mean (Std. Err.)
region4	=1 if the farm is located in the Prairie Gateway region, 0 otherwise	0.125 (0.331)
region5	=1 if the farm is located in the Eastern Uplands, 0 otherwise	0.078 (0.269)
region6	=1 if the farm is located in the Southern Seaboard region, 0 otherwise	0.126 (0.332)
region7	=1 if the farm is located in the Fruitful Rim region, 0 otherwise	0.163 (0.369)
region8	=1 if the farm is located in the Basin and Range region, 0 otherwise	0.035 (0.183)
region9	=1 if the farm is located in the Mississippi Portal region, 0 otherwise	0.041 (0.198)
internet	= 1 if the farm has internet access, 0 otherwise	0.763 (0.425)
organic_farm	Number of organic farms in the county where the farm is located	13.792 (35.252)
distance	Distance from farm to the nearest town or city with population of 10,000 or more	24.186 (23.373)
ds_farms	Number of direct-marketing farms in the county where the farm is located	46.102 (106.163)
fmrkt11	Number of Farmers market in the county in which the farm is located	2.86 (5.771)
hiredhours	Hired labor hours	5145.587 (113077)
acres	Number of acres operated in farm	1068.118 (3038.868)
govtpmt	= 1 if farm receive government payment, 0 otherwise	0.553 (0.497)

Table 4.3 Organic Farming and Direct Marketing Adoption Estimation

	Organic Farming Adoption		Direct Marketing Adoption	
	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.
DM	-0.005	(0.106)		
Org			-1.763***	(0.547)
cgrain	-0.019***	(0.006)	-0.062***	(0.016)
hvc	0.026	(0.027)	0.279***	(0.027)
mdairy	0.001	(0.010)	-0.047**	(0.020)
oanimal	-0.013**	(0.005)	0.000	(0.014)
intermediate	0.000	(0.007)	-0.026	(0.016)
commercial	-0.006	(0.009)	-0.066***	(0.016)
region2	0.002	(0.009)	0.057***	(0.013)
region3	-0.002	(0.005)	-0.018	(0.014)
region4	-0.005	(0.004)	-0.035***	(0.008)
region5	-0.008*	(0.004)	-0.034***	(0.011)
region6	-0.002	(0.003)	-0.013	(0.010)
region7	-0.010	(0.007)	-0.064***	(0.013)
region8	0.015*	(0.009)	0.061***	(0.022)
region9	-0.006	(0.004)	-0.033***	(0.009)
age	-0.000***	(0.000)	-0.002***	(0.000)
male	-0.005	(0.006)	-0.043***	(0.016)
edu2	-0.016**	(0.008)	-0.071***	(0.017)
edu3	-0.009	(0.007)	-0.046***	(0.016)
edu4	-0.002	(0.006)	-0.006	(0.016)
occ_farming	0.008	(0.006)	0.041**	(0.016)
offwork	0.001	(0.003)	0.000	(0.007)
entropy	0.036*	(0.021)	0.230***	(0.034)
prd_contract	-0.001	(0.004)	-0.011	(0.011)
mkt_contract	-0.003	(0.004)	-0.034***	(0.008)
internet	-0.004	(0.003)		
organic_farm	0.0004***	(0.00008)		
distance			-0.0002	(0.00013)
ds_farms			0.0002**	(0.00006)
fmrkt11			0.002*	(0.001)
_cons	0.056***	(0.021)	0.255***	(0.040)
N	14960		14960	

Standard errors in parentheses are adjusted for heteroscedasticity.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.4 Gross Farm Income Estimation

	Coef.	Robust Std. Err.
pre_org	2.163***	(0.768)
pre_dm	-0.002	(0.043)
cgrain	0.561***	(0.043)
hvc	0.749***	(0.060)
mdairy	0.820***	(0.053)
oanimal	0.224***	(0.042)
intermediate	0.626***	(0.048)
commercial	2.627***	(0.051)
region2	-0.098***	(0.030)
region3	0.149***	(0.050)
region4	-0.044	(0.033)
region5	-0.146***	(0.036)
region6	-0.213***	(0.031)
region7	0.230***	(0.035)
region8	-0.046	(0.058)
region9	0.087**	(0.039)
age	-0.005***	(0.001)
male	0.270***	(0.040)
edu2	0.136***	(0.039)
edu3	0.121***	(0.039)
edu4	0.221***	(0.039)
occ_farming	0.124***	(0.044)
offwork	-0.051**	(0.020)
entropy	0.975***	(0.077)
prd_contract	-0.134***	(0.038)
mkt_contract	0.433***	(0.020)
hiredhours	0.001***	(0.000)
acres	0.061***	(0.016)
govtpmt	0.501***	(0.023)
_cons	9.422***	(0.095)
N	14802	

Standard errors in parentheses are adjusted for heteroscedasticity.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Chapter 5 Summary and Conclusions

This dissertation examines three issues in organic food marketing, accounting for the dynamic marketing environment the organic food sector is in. Chapter 2 examines household demand relations of milk categories differentiated by organic status and brand types in the U.S. with an almost ideal demand system approach. The main conclusion is that fluid milk, as a whole product group, is an inferior good and asymmetric substitution patterns exist between conventional milk and organic milk, and between private label milk and branded milk. The implications of these findings are twofold. First, it confirms the strong demand for organic milk among the U.S households, and highlights the importance of ensuring sufficient supply, especially given the short supply of organic feedstock in the industry in recent years. Second, though the private label conventional milk has the largest share among all milk types, households tend to substitute it for branded milk and organic milk. Given this result, it is advisable that retailers of private label milk engage in more product differentiation, including providing organic milk for their private labels.

Chapter 3 answers the question whether households' preference for organic food affect their choice of retail stores in their grocery trips. As organic food becomes more widely available in mainstream retailers, which compete in the organic sector, households may have different perception about retail formats marketing organic food. Californian Households' choice of retail formats is modeled with a conditional logit model. Main results are households' organic preference affect their retail format choice, and regular organic user households are more likely to patronage organic specialty stores and discount stores, but less likely to shop in warehouse clubs. Price, consumer loyalty, and household shopping behavior also have the expected effects on household retail format choice. This result indicates the importance of the retail sector in the organic food supply chain. Also for the organic producers and processors, the choice of retail formats should be one of their considerations.

Chapter 4 explores the linkage between farmers' adoption of organic farming and direct marketing practices, given the increasing popularity of local food among consumers and governmental rural development policies promoting direct marketing. The understanding of this linkage could facilitate the current government programs and policies in promoting both organic agriculture and direct marketing. A bivariate linear probability model is estimated to investigate this linkage. The main result is that farmers' adoption of organic farming reduced the probability of their adoption direct marketing while the effect of farmers' adoption of direct marketing on their organic farming adoption is negative yet weak. This result indicates a substitution relation between the two practice, and thus necessity to integrate programs in promoting organic farming and direct marketing. The effects of the two practices on gross farm income are also evaluated, and the positive effect of organic farming is found while no statistically significant effect for direct marketing. This suggests the economic sustainability of organic farming.

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