Retail and Wholesale Market Power in Organic Foods

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Abstract:

The demand for organic fresh fruits and vegetable continues to grow at a rate far higher than the rest of the produce industry. The cost of meeting organic certification standards, however, has meant that supply has been slow to adjust. With limited supply, we hypothesize that organic suppliers enjoy more market power in bargaining over their share of the retail-production cost margin for fresh apples. We test this hypothesis using a random parameters, generalized extreme value demand model (mixed logit) combined with a structural model of retail and wholesale pricing that allows conduct to vary by product attributes (organic or non-organic) and time. We find that organic growers do indeed earn a larger share of the total margin than non-organic growers, but this vertical market power is eroding over time as market supply adjusts.

keywords: organics, market power, mixed logit, game theory, non-linear pricing**.**

JEL Codes: C35, D12, D43, L13, L41, Q13.

Introduction

The margin earned on organic relative to conventional agricultural products is a critical variable in determining the future growth of organic supply (Ehmke, et al., 2004). From a grower's perspective, organics represent an opportunity to develop a "value added" strategy without investing in processing facilities. Adopting organic production methods, however, requires an investment in both new knowledge and equipment and abandoning relatively low-cost chemical-based practices. Clearly, margins for organic produce must be sufficiently high to make the investment worthwhile. Organic produce currently sells for a significant premium over non-organic produce in most categories, but it is not clear whether these high prices are due to retailers exploiting strong consumer demand, or if retail prices simply reflect higher production costs. If retailers are exploiting what monopsony buying power they may possess to keep farm prices for organic produce low, then supplier margins are not likely to justify further growth in the industry. On the other hand, if the limited supply of organic produce provides suppliers with a measure of market power, then further investment is likely and retail-farm margins should decline over time (Oberholtzer, Dimitri and Greene, 2005). Which of these two outcomes is consistent with the existing data is the empirical question that this study seeks to resolve.

Organic food products represent perhaps the most significant innovation in the food and agriculture industry in the last 30 years. Between 2005 and 2006, organic food sales in the U.S. rose 22% from \$13.8 billion to \$17.0 billion (Organic Consumers Association). While relatively mature organic categories grew only modestly over this period (organic fruits and vegetables, 7.0%) other categories are growing much more rapidly on a smaller sales base (dairy products, 27.0%). Nonetheless, fruits and vegetables accounted for \$4.3 billion (42%) of the organic food market in 2003 and were expected to grow to $8.5 billion by 2010 (Nutrition Business Journal). Consumer surveys show that this trend is largely driven by market demands for food that is perceived to be free of chemical residue, is more environmentally friendly, supports local farmers and is more likely to be free of pathogens that lead to food-borne diseases (Thompson, 1998; Whole Foods, 2004). At least initially, organics offered many retailers an opportunity to differentiate themselves from traditional supermarkets – witness the rapid growth of Whole Foods and Wild Oats (since merged) during the 1990's and early 2000's. In most retail markets, organics carry significant price premiums (Lohr,1998; Huang and Lin, 2007). Premium prices, however, do not necessarily imply high margins.

There is some question in the literature as to which party in the food supply chain – retailers or suppliers – possesses bargaining power in their relationship with the other.[1] While it may be the case that suppliers can exercise vertical market power when products are being promoted (Richards and Patterson, 2005), when there is a short harvest (Sexton and Zhang, 1996) or for a number of other reasons (Draganska and Klapper, 2007), retail concentration can lead to buying power on the other side (Inderst and Shaffer, 2007). When the conditions that lead to supplier market power are transitory, however, excess margins can be short-lived. Such is believed to be the case with organic food products (Blank and Thompson, 2004; Oberholtzer, Dimitri and Greene, 2005), particularly when price and availability are regarded by consumers as the top-two most critical barriers to purchasing more organic produce (Hartman, 2002). Sales of

[1] Among recent studies that use a similar approach to that used here, Berto Villas-Boas (2007) finds that yogurt wholesalers price at marginal cost and retailers set profit-maximizing prices, while Bonnet, Dubois and Simioni (2006) cannot reject a model in which wholesalers exercise retail price maintenance in the French bottled water market.

organic products in virtually all categories continue to grow at double-digit rates, despite anecdotal evidence that the supply of truly organic products in many categories is chronically short. At the same time, many retailers rely on a consistent supply of high-quality organic products to help remake their image as innovative, current and in-tune with changing consumer tastes (The Packer). The empirical analysis described in this paper tests whether these conditions lead to higher or lower supplier margins for organic apples in the U.S. Specifically, we seek to empirically examine the impact of introducing organic products on vertical market power exercised by suppliers within traditional grocery product supply chains.

The paper is organized as follows. The next section describes a structural econometric model of the U.S. fresh apple market, including both the retail and supply sectors. The second section describes the data used in the analysis and the estimation methods used to implement the econometric model. A third section presents the estimation results and calculations concerning the allocation of operating margins between retailers and suppliers. A fourth section concludes and draws some implications for other organic and non-organic product markets.

Econometric Model of Organic Apple Pricing

We model the market for organic and non-organic apples using a structural model of consumer, retailer and supplier (wholesaler, or packer) behavior. Retailers and suppliers are assumed to behave strategically in their horizontal and vertical interactions. To model these interactions, our framework consists of consumer demand and retail / wholesale pricing models that are estimated sequentially.

Consumer Demand

Consumer demand is represented by a random utility specification in which consumers are assumed to make a discrete choice of one apple variety from among those represented in our retail data sample, or some other apple variety from another outlet. This latter alternative is defined as the outside option. The utility consumer *i* obtains from consuming product *j* during week *t* is a function of the product's price (p_{jt}) and mean level of utility, or product-specific preferences, γ_{ijt}, and a set of individual-specific attributes (z_{il}):

$$u_{ijt} = \gamma_{ijt} + \alpha_i p_{ijt} + \sum_l \eta_l z_{il} + \xi_{jt} + \varepsilon_{ijt}, \tag{1}$$

where ξ_{jt} is an error term that accounts for all product-specific variation in demand that is unobserved to the researcher such as the appearance of the apples, the internal or eating quality, the amount of shelf-space allocated to each variety or unmeasured advertising, and ε_{ijt} is an i.i.d. type I extreme value error term that accounts for consumer-specific heterogeneity in preferences. With this error assumption, the utility specification in (1) implies a logit discrete choice demand model.

Because each variety is available in both organic and non-organic form, however, we extend the simple logit model to consider the hierarchical nature of a consumer's choice process: consumers first choose whether to buy an organic or non-organic apple, and then the specific variety. Consequently, we modify the distributional assumption governing ε_{ijt} by allowing it to follow instead a Generalized Extreme Value (GEV, McFadden, 1978) distribution. With the GEV assumption, we allow for differing degrees of substitution among products within each group: organics and non-organics. In terms of the utility model introduced in (1), the GEV extension involves including a composed error such that:

$$u_{ijt} = \gamma_{ijt} + \alpha_i p_{ijt} + \sum_l \eta_l z_{il} + \xi_{jt} + \tau_{ijt} + (1 - \sigma_J)\varepsilon_{ijt}, \tag{2}$$

where τ_{ijt} is an error-component (Cardell, 1997) that makes the entire term: $\tau_{ijt} + (1 - \sigma_J)\varepsilon_{ijt}$ extreme-value distributed as well. The aggregate probability that consumer *i* purchases product *j* in group *J* (organic or non-organic from a retail supermarket) or the market share, is given by the product of the conditional probability of buying within a particular group and the probability of the group as a whole, or:

$$s_j = s_{j|J} s_J = \frac{e^{(\delta_j + \varphi_i)/(1 - \sigma_J)}}{D_J^{\sigma_J}[\sum_J D_J^{(1 - \sigma_J)}]}, \tag{3}$$

where δ_j is the mean utility of product *j*, or the part of utility that does not vary over consumers, and φ_i is the part that does, $s_{j|J}$ is the share of product *j* among either the organic or non-organic group, s_J is the share of group *J* in overall apple sales, and $D_J = \sum_{j \in J} e^{(\delta_j + \varphi_i)/(1 - \sigma_J)}$ represents the inclusive value from purchasing from group *J* so that $s_J = D_J^{1 - \sigma_J} / \sum_J D_J^{1 - \sigma_J}$. Faced with a total market size of *M*, therefore, the quantity sold of product *j* is written as: $Q_{jt} = s_{jt} M$.

As is well known, however, the GEV model still suffers from the independence of irrelevant alternatives (IIA) property within groups, which means that the substitution elasticities between products depends only on their market shares and not on more fundamental attributes that are likely to influence demand. Consequently, we allow the product-preference and marginal utility of income parameters in (3) to vary over consumers in a random way (Berry, Levinsohn and Pakes (BLP), 1995; Nevo, 2001; McFadden and Train, 2000). Specifically, the marginal utility of income is normally distributed over consumers so that:

$$\alpha_i = \alpha + \sigma_\alpha \nu_i, \quad \nu_i \sim N(0,1), \tag{4}$$

where α is the mean price response across all consumers and ν_i is the consumer-specific variation in response with parameter σ_α. Similar to Erdem (1996) and Nair, Dube, and Chintagunta (2005), we also assume that product-specific preferences depend on the attributes (x_{jk}) of each product, j:

$$\gamma_{ijt} = \sum_k \beta_{ik} x_{jk}, \quad k = 1,2,\ldots K. \tag{5}$$

where the attributes include a constant term (γ_{iot}), a binary discount variable (d_j) that assumes a value of 1.0 if the product is reduced in price by at least 10% from one week to the next, and then returned to its previous value in the following week, an interaction term between the discount and price ($d_j p_j$) and a time trend, t. Consumers are assumed to differ in their preference for each product attribute so that unobserved consumer heterogeneity is reflected in the distribution of each nutrient's marginal utility:

$$\beta_{ik} = \beta_k + \sigma_\beta \mu_{ik} \quad \mu_{ik} \sim N(0,1), \quad k = 1,2,\ldots K. \tag{6}$$

McFadden and Train (2000) interpret the elements of (6) in terms of an error-components model of attribute demand. In contrast to the IIA property of a simple logit model, the heterogeneity assumption in (6) creates a general pattern of substitution over alternatives j through the unobserved, random part of the utility function given in (1). As a result, the utility from different apple varieties is correlated according to their set of attributes included in $\boldsymbol{x}_j$. Non-IIA substitution is critical in models of differentiated product pricing because inferences regarding either upstream or downstream market power would otherwise be entirely confounded by mis-estimates of the partial elasticity of demand facing each product.

With a discrete choice model of demand, it is assumed that each consumer purchases only one unit of the chosen product. Because our data measures aggregate market shares, therefore, we aggregate over the distribution of consumer heterogeneity to arrive at an expression for the share of each apple variety out of the entire market for apples. Essentially, market share is the sum of individual purchase probabilities for each product. Because the mixed logit model introduces a large number of parameters relative to the simple logit model, we follow Nevo (2001), among others, and write the indirect utility function in terms of two sets of variables – those that are assumed to be random and those that are not:

$$u_{ijt} = \delta_{jt}(p_{jt}, x_j, z_l, \xi_{jt}; \gamma, \alpha, \eta, \sigma_j) + \varphi_{ijt}(p_{jt}, \nu_i, \mu_{ik}; \sigma_\alpha, \sigma_\beta) + \varepsilon_{ijt}, \qquad \textbf{(7)}$$

where δ_{jt} is the mean level of utility that varies over products, but not consumers, and φ_{ijt} is the idiosyncratic part that varies by consumer and product. Define the densities of μ_{ik} and ν_i as $f(\mu)$ and $g(\nu)$, respectively, so that the market share of product j, obtained by integrating over the distributions reflecting consumer heterogeneity, becomes:

$$s_{jt} = \int\int \frac{e^{(\delta_{jt} + \varphi_{ijt})/(1-\sigma_J)}}{D_J^{\sigma_J}(\sum_J D_J^{1-\sigma_J})} f(\mu) g(\nu) d\mu d\nu, \tag{8}$$

which can then be estimated in aggregate data using simulated maximum likelihood (SML) algorithms (Train, 2003). Simulation methods are required to estimate the demand-side model because there is no closed form-expression for market share as in the simple logit case (Berry, 1994).

Organic Produce Pricing Game

While there are few recognized brands in the U.S. apple market, we assume apples are differentiated by variety. Therefore, we assume the wholesale sector consists of several suppliers – one for each apple variety. Given the aggregate nature of our retail data, we characterize the organic marketing channel as consisting of a single, multi-product retailer, and multiple suppliers. Although there are clearly many suppliers and retailers in reality, we gain nothing by modeling individual behavior, because our focus is on market power relationships between the retail sector and consumers downstream, and retailers and suppliers upstream. Consistent with the literature on retail pricing, the retailer behaves as a Stackelberg follower: the suppliers specify wholesale prices given their expectations of how the retailer will respond, and the retailer then sets prices paid by consumers. We solve for the sub-game perfect Nash equilibrium in the usual way: by working backward from the retailer to the suppliers' problem.

Beginning with the retailer decision, and suppressing the time period index (t) for clarity, the retailer sets a price for each product, p_j, each week to solve the following problem:

$$\Pi^r = \max_{p_j} M \sum_{j=1}^{J} (p_j - r_j - w_j) s_j, \qquad \textbf{(9)}$$

where M is total market demand, w_j is the wholesale price, r_j are unit retailing costs, and s_j is the market share defined above.[2] Retailing costs are assumed to be constant, which is plausible given the share of store-sales accounted for by any individual product. Under the manufacturer-Stackelberg assumption, the retailer sets prices taking wholesale prices as given.

We assume the retailer sets prices recognizing the interrelated nature of differentiated product demand such that he or she internalizes all intra-store pricing externalities (behaves as a perfect category manager). Consequently, the retailer's first-order condition for product j is given by:

$$s_j + \sum_{k=1}^{J} \frac{\partial s_k}{\partial p_j} (p_k - r_k - w_k) = 0, \quad j = 1, 2, \ldots, J, \qquad \textbf{(10)}$$

for all J products in the store. Stacking the first-order conditions for all products and solving for retail prices in matrix notation gives:

$$\boldsymbol{p} = \boldsymbol{r} + \boldsymbol{w} - \boldsymbol{S}_{\boldsymbol{p}}^{-1} \boldsymbol{S}, \qquad \textbf{(11)}$$

where $\boldsymbol{p}$ is an J x 1 vector of prices, $\boldsymbol{w}$ is a J x 1 vector of wholesale prices, $\boldsymbol{r}$ is a J x 1 vector of

[2] We refer to the wholesale price throughout as the price nearest the grower. In our data, the wholesale price is defined as a "packing-house door" price, so represents grower returns plus packing and handling costs.

product-specific retailing input prices, $\boldsymbol{S}$ is an J x 1 vector of market shares, and $\boldsymbol{S_p}$ is a J x J matrix of share-derivatives with respect to all retail prices. Because the suppliers take the retailer's optimal response into account in setting upstream prices, equation (11) represents the retail decision rule that frames their pricing decisions.

Suppliers are assumed to set wholesale prices in order to maximize the surplus over production costs for the product they sell, conditional on the retailer's response. Again assuming each supplier packs only one of the varieties sold by the retailer, the profit maximization problem faced by supplier j is given by:

$$\Pi_j^m = \max_{w_j} M(w_j - c_j)s_j, \qquad \textbf{(12)}$$

where c_j is the (constant) production cost of product j incurred by the supplier and the other variables are as described above. The first-order conditions for the supplier have to take into account the effect of changes in the price of product j and all other prices so are written as:

$$s_j + \sum_{k=1}^{J} \frac{\partial s_j}{\partial p_k} \frac{\partial p_k}{\partial w_j}(w_j - c_j) = 0, \quad j = 1,2,...,J, \qquad \textbf{(13)}$$

which is simply an expression of the supplier's vertical pricing problem taking the retailer's best reply into account. As in Sudhir (2001) and Villas-Boas and Zhao (2005), we derive expressions for the wholesale price derivatives (pass-through rates) by totally differentiating the retail first-order conditions to find:

$$\sum_{k=1}^{J}\frac{\partial s_j}{\partial p_k}\frac{\partial p_k}{\partial w_j} + \sum_{k=1}^{J}\sum_{l=1}^{J}(p_l - r_l - w_l)\left(\frac{\partial^2 s_l}{\partial p_j \partial p_k}\right)\frac{\partial p_k}{\partial w_j} + \sum_{l=1}^{J}\frac{\partial s_l}{\partial p_j}\frac{\partial p_l}{\partial w_j} = \frac{\partial s_j}{\partial p_j} \quad \forall \quad j = 1,2,\ldots J, \tag{14}$$

which can be simplified by defining a J x J matrix $\boldsymbol{G}$ with typical element g_{jk} such that:

$$g_{j,k} = \frac{\partial s_j}{\partial p_k} + \sum_{l=1}^{J}(p_l - r_l - w_l)\left(\frac{\partial^2 s_l}{\partial p_j \partial p_k}\right) + \frac{\partial s_k}{\partial p_j}. \tag{15}$$

Using this expression to write the wholesale margin becomes:

$$\boldsymbol{w} - \boldsymbol{c} = -((\boldsymbol{G}^{-1}\boldsymbol{S_p})\boldsymbol{S_p} * \boldsymbol{I_N})^{-1}\boldsymbol{S}, \tag{16}$$

where $\boldsymbol{I}_N$ is a J x J identity matrix and * indicates element-by-element multiplication.

To this point, all of parameters required to identify the equilibrium margins are contained in the demand side estimates ($\boldsymbol{S}_p$ and $\boldsymbol{G}$) and from the estimated marginal cost functions.[3] Marginal retailing and wholesaling costs, in turn, are estimated as linear functions of input prices, $\boldsymbol{v}_r$ and $\boldsymbol{v}_w$ such that: $\boldsymbol{r}(\boldsymbol{v_r}) = \gamma_{r0} + \sum_{i=1}^{I}\gamma_{ri}v_{ri}$, and $\boldsymbol{c}(\boldsymbol{v_w}) = \gamma_{w0} + \sum_{l=1}^{L}\gamma_{wl}v_{wl}$ for retailing and wholesaling costs, respectively. These functions are estimated after substituting the demand parameters into (11) and (16) in the two-step procedure described below.

[3] Detailed derivations of each matrix are available from the authors, but are similar to Villas-Boas and Zhao (2005) and Berto Villas-Boas (2007). Note that these parameters are also interpreted as measuring the extent of deviation from the maintained behavioral assumption - monopoly for the retailer and Bertrand-Nash for the suppliers.

Retailer and Supplier Behavior

In this model, the implicit assumption is that both the retailer and suppliers optimize according to the structure of the game and, as such, there is no deviation from the theoretical equilibrium. As Villas-Boas and Zhao (2005) and Draganska and Klapper (2007) suggest, however, there is likely to be asymmetrical market power relationships or other factors that cause the actual outcomes to differ from these theoretical expectations. We hypothesize that the critical factor to consider is whether a supplier sells organic or conventional produce. Therefore, we allow for deviations from either the profit-maximizing monopoly choices on the part of the retailer or the Bertrand-Nash decisions by the suppliers by introducing parameters in (11) and (16) that measure the deviation of the retail margin ($\boldsymbol{\varphi}$) and supplier margin ($\boldsymbol{\theta}$) from the maintained assumption:

$$\boldsymbol{p} - \boldsymbol{w} - \boldsymbol{r} = -((1/\varphi)\boldsymbol{S_p})^{-1}\boldsymbol{S}, \tag{17}$$

for the retailer, and:

$$\boldsymbol{w} - \boldsymbol{c} = -\theta((\boldsymbol{G}^{-1}\boldsymbol{S_p})\boldsymbol{S_p} * \boldsymbol{I_N})^{-1}\boldsymbol{S}, \tag{18}$$

for the suppliers. We allow each deviation parameter to depend on whether a product is organic or non-organic to test our hypotheses regarding the effect of organic status on margin behavior. Therefore, both parameters are written as linear functions of a constant term, a binary indicator of organic-status and a time-trend variable interacted with the organic binary variable: $\varphi_j = \varphi_0 + \varphi_1 O_j + \varphi_2 O_j t$, and $\theta_j = \theta_0 + \theta_1 O_j + \theta_2 O_j t$, where O_j takes a value of 1 if a supplier or retailer sells organic produce and 0 otherwise. If $\varphi_1 > 0$, then the retailer earns higher margins on organic products in the downstream market than non-organics. Similarly, if $\theta_1 > 0$ then an organic supplier earn higher margins upstream. If organics are in short supply as media reports suggest, then the supplier holds the upper hand in bargaining over the allocation of surplus generated through the retail sale, or the total margin between the consumer and grower. Further, if $\varphi_2 < 0$ then any organic-premium earned by the retailer erodes over time, or if $\theta_2 < 0$ then the supplier's market power declines over time. Calculating fitted values of each deviation parameter allows us to test the maintained structure of the game (Villas-Boas and Zhao, 2005; Draganksa and Kapper, 2007). Namely, if: $\hat{\varphi}_j(\hat{\theta}_j) > 1$ then the retailer (suppliers) price above the assumed level, and if: $\hat{\varphi}_j(\hat{\theta}_j) < 1$ then the retailer (suppliers) price below the level consistent with the solution assumptions described above. Of course, values of either parameter equal to zero suggest a situation in which neither seller – either at the retail or wholesale level – takes into account the markup available from selling differentiated products. In this case, margins are equal to zero and perfect competition on a product-by-product basis ensues. We test for each of these possible outcomes using the retail and wholesale data described next.

Data Description: Fresh Apples

Data Description

Retail volume and shipment data for this study are from Fresh Look Marketing, Inc., and describe shelf prices and retail volume movement on a weekly basis from January 1, 2005 through December 31, 2007. Both prices and shipments are measured at a market-aggregate level for five metropolitan statistical areas (Atlanta, Chicago, Dallas, Los Angeles and New York). In each case, the market aggregate is comprised of all major retailers that participate in retail scanner syndication programs, consequently we do not measure sales through club stores or supercenters that do not participate. Over the five markets, the all-commodity volume (ACV), or share of the market included in the scanner data, is 71.0%.

Grower prices for both organic and regular apples (FOB) are from the Washington Growers Clearing House (WGCH), which is the primary repository for grower-level price and shipment data for all fruit shipped in the state of Washington. Prices include both regular and controlled-atmosphere shipments, so the prices used for this study represent a weighted average of both regular and controlled atmosphere, and are defined as packing-house door prices.

Table 1 summarizes both the retail and grower apple price data. Our observations that motivate this research and as described in the introduction are confirmed by inspecting the data shown here. Specifically, the market share for each organic variety is only a fraction of the non-organic equivalent, but both retail and wholesale prices are far higher for most organics relative to non-organics. Although retail-farm price spreads are only imperfect measures of the retail margin for the reasons described in Chintagunta, Bonfrer and Song (2002), comparing the retail-farm price spreads in this table suggest that suppliers may enjoy some sort of leverage over their retail buyers as the absolute and relative spreads are far higher than for non-organics.[4] These margins, however, may be absorbed by higher production and distribution costs, so testing the

[4] Namely, the prices reported by retailers, and as reported by the WGCH in this case, do not reflect retailer-specific deals, quantity discounts and other non-invoice items that are typically part of the contract terms.

central hypotheses of the paper requires a more detailed statistical analysis that takes each type of cost into account.

[table 1 in here]

The input prices used to estimate the marginal cost function also serve as instruments (interacted with market binary variables) in estimating the margin equations. Because we estimate marginal retailing and production costs, we need two sets of input prices. Retailing costs are assumed to depend on labor and energy prices. Labor costs are represented by wages earned by supermarket laborers and retail managers. Both series are from the Bureau of Labor Statistics (BLS). Energy prices are proxied by electricity price indices for each market in the retail data set and are also from the BLS. Production cost, on the other hand, is determined by a number of inputs used in agricultural production: farm labor wages, and prices for fertilizer, chemicals, fuels, supplies and services. Each of these indices is from the Economic Research Service of the USDA (ERS). Because of the short time period covered by our data, adjusting for inflation made no difference to the estimation results.

For the mixed logit model, demographic data are required for each market in order to describe the observed heterogeneity among households. Because we do not have household-level data, however, we follow the convention in this literature (Berto Villas-Boas, 2007; Nevo, 2001) and draw demographic data randomly from each of our sample markets using the Current Population Survey (CPS) from the Bureau of Census. From the available data, we choose age, education (highest level attained) and household income as the primary demographic descriptors. In the empirical model, it was found that only age and education contribute significantly to the variation in product-specific preferences over time.

In models of strategic pricing behavior, the variables of interest are typically endogenous, both in the demand and pricing models. For the demand model, we estimate the mixed logit model using simulated maximum likelihood. Because this is a full information method, it provides consistent estimates when the set of explanatory variables may include endogenous variables. In this case, retail prices are endogenous. With respect to the pricing model, however, we estimate using an instrumental variables approach in order to identify the conduct parameters when both retail and wholesale margins are endogenous. For this purpose, we require instruments that are correlated with the endogenous variables, but not the unobservables in the pricing equation. Unobservable factors that are likely to influence marketing margins for apples include such things as local transportation or supply constraints, variation in apple quality, the amount of exports entering the local market or marketing strategies specific to individual distributors that are obscured in the aggregate data. Following others in this literature (Berto Villas-Boas, 2007; Draganska and Klapper, 2007) we use a variety of instruments. First, we interact retail and production input prices with the set of market binary variables. Market-specific variation in costs will be correlated with prices in the same market, but not likely to be correlated with unobservable factors in the margin equations. Second, we include a set of lagged share and margin values in order to pick up any pre-determined pricing effects. Third, we include product-specific binary variables to account for idiosyncratic supply or quality factors that are unobservable to the econometrician but are clearly important in determining either wholesale or retail margins.

Estimation Method

The demand model is estimated using the method of simulated maximum likelihood (SML, Train, 2003). SML uses Monte Carlo simulation to solve the integral in (8) up to an approximation that is accurate to the number of random draws chosen, R. This method provides consistent parameter estimates under general error assumptions and is readily able to accommodate complex structures regarding consumer heterogeneity. In order to speed the estimation process, we simulate the multi-dimensional integral that defines the distribution of heterogeneity using R draws from a Halton sequence (Train, 2003; Bhat, 2003). We find that R = 50 draws are sufficient to produce stable estimates without excessive estimation time. Bhat (2003) provides experimental evidence that shows Halton sequences can reduce the number of draws required to produce estimates at a given accuracy by a factor of 10. For the margin equations, we use Generalized Method of Moments (GMM) in order to account for the endogeneity of retail and wholesale that are calculated from the first-stage SML estimates. We estimate equations (17) and (18) together as a set in order to take advantage of the efficiency gains associated with any contemporaneous correlation between the equations. Sequential estimation of the demand and margin equations in this way is common in the literature and has been shown to differ little from simultaneous estimation (Villas-Boas and Zhao, 2005). Further, we restricted the mean conduct parameter to be equal for all varieties because they are sold under the same game structure. Conduct, therefore, varies over time and by organic status (organic or non-organic).

Results and Discussion

In this section, we first present and discuss the demand-system estimates, and then tests of the central hypotheses of the paper with, first, a model that includes only retail margins, and then a second model that includes both retail (downstream) and wholesale (upstream) margins.

As a first step in interpreting the demand model results, we test the validity of the random-parameter GEV model against both a simple logit model and a GEV model with constant parameters. Testing a GEV model against a simple logit alternative involves the GEV scale parameter, σ_J. If $\sigma_J = 0$, then the GEV model collapses to a simple logit. In the results shown in table 2, the t-statistic for the null hypothesis that $\sigma_J = 0$ is 204.401 so we easily reject the null hypothesis and conclude that the GEV model is preferred. Next, we compare the random-parameter GEV to a constant parameter alternative. For this purpose, we use a likelihood ratio test where the constant parameter model is the restricted and the random parameter the unrestricted version. The LR statistic for this test is 8,042.46, so with 7 degrees of freedom we again reject the simpler for the more comprehensive model. Other specification tests evaluate the specific form of the random parameter GEV specified here. Clearly, the options for specifying the nature of the heterogeneity driving product-specific preferences and the marginal utility of income are nearly limitless. In the current application, we allowed the constant term of the product-specific preference parameter, γ_{i0}, to vary by age and income. The results in table 2 show that the education effect is significant at a 5% level, but age is only significant at 15%. However, heterogeneity in the marginal utility of income – the price parameter – depends significantly on both age and education. Moreover, the scale parameters for both the price and constant terms are significantly different from zero. Therefore, we can conclude that the random parameter model is preferred to the constant-parameter alternative so will use this version to interpret the demand results.

In the demand model, the key parameters of interest are the own-price effect, the discount-effect, the discount-price interaction and the GEV scale parameter. The own-price effect – measured by the marginal utility of income – is non-positive, as expected, and increases with both age and education. Temporarily discounting apples in the current week causes demand to shift outwards and rotate clockwise, or become less elastic. This is also an expected result and suggests that apples, in general, are conducive to price promotions. Among other variables included in the demand model, the time-trend indicates that the demand for apples is moving upward, albeit slowly, over time. Given that New York is the excluded market variable, apples in all other markets except Los Angeles have a lower share than in New York. Further, the variety-specific effects suggest that all varieties have lower marginal shares (share of the total apple market) than regular Red Delicious apples. Finally, the GEV scale parameter represents a measure of the extent to which apples substitute for each other within a market, where 1.0 indicates perfect substitutability. From the estimate in table 2, it is clear that apples are highly substitutable for each other in general, but more specific information on the degree of substitutability, however, is provided in the elasticity matrix (table 2a).

[table 2a in here]

Perhaps the most important thing to notice from the matrix of elasticities is that the random parameter GEV model is not subject to the IIA problem. Non-constant cross-price elasticities show that correlation in demand across varieties driven by the random parameter assumption causes like products to be more substitutable than those that are fundamentally different. Organic apples are relatively weak substitutes for each other, while non-organic apples are more readily substitutable. It is also apparent from these results that all apple varieties are elastic in demand, and there appears to be little difference between organic and non-organic apples in terms of their demand elasticity. This is somewhat surprising, but could represent one indication that the organic apple market is beginning to mature.

[table 2b in here]

The demand estimates shown in table 2a are then used to recover estimates of the retail and wholesale margins according to equations (17) and (18) and subsequently used to estimate the extent to which retailers or suppliers are able to capture margins that are different from zero. That is, if the estimates of φ differ from zero, then the retailer earns greater margins than are implied by monopoly pricing in a multi-product context (category management), and if θ differs from zero, suppliers earn above-competitive margins.

We begin by estimating equation (17) on its own in order to demonstrate how retail margins behave for organics and non-organics if supplier relationships are not taken into account. Estimates of this model are shown in table 3, while table 4 presents the estimates from a more complete model of vertical and horizontal competition. Table 3 provides estimates from both least-squares and GMM estimates. Because a Wu-Hausman endogeneity test strongly rejects the null hypothesis that retail margins are exogenous (chi-square = 45.67 compared to a critical value at 5.0% of 3.84) we know that the GMM estimator is appropriate, but we present both sets of results to demonstrate the extent of bias that results when endogeneity is ignored. Both sets of estimates suggest that retail margins for non-organic apples in the base time period ($t = 0$) are far more competitive than the maintained multi-product monopoly equilibrium, but are still above the zero-margin benchmark. Comparing the least squares and GMM estimates, the former shows only a slight, yet statistically significant, deviation from the perfectly competitive level, while the GMM estimates imply a difference near five times as large (0.037 versus 0.164). Further, the least squares estimates find an "organic effect," or the difference between the deviation of organic and non-organic retail margins from the maintained pricing assumption, approximately one-fifth that of the GMM estimates. Both estimators, however, find a small upward trend in the organic effect, albeit significant only at a 10.0% level. Because these results do not take into account retailer interactions with the supplier, however, they are only partial estimates of how organic and non-organic margins compare over time.

[table 3 in here]

A more complete picture is provided by the estimates in table 4, which introduces supplier margins and vertical competition. The results in this table, which are generated using the GMM estimator given the endogeneity-test results cited above, show that the retail margins for non-organic apples in the base time period are much closer to the maintained monopoly assumption (less competitive) than supplier margins (0.495 > 0.078). This result likely reflects the general insight that retailers provide more value-added over wholesale acquisition cost than do suppliers over their own growing costs. Value-added, in this case, is broadly defined to include not only time- and place-utility, but market power that derives from advertising, concentration and other factors. More importantly, however, the results in table 4 show that retail margins are more competitive for organic apples relative to regular apples, while supplier margins are far closer to the Nash assumption for organic apples compared to regular apples. Combined, these estimates support our initial hypothesis that a shortage in organic apple supply has shifted bargaining power from retailers to suppliers for organic apples. Retail margins are lower for organic apples in part because consumers regard prices of organic produce to be critical barriers to trial and usage. In order for retailers to help their new organic strategies to succeed, which are necessary from a broader strategic perspective, they have to charge relatively low prices on organic produce to induce new consumers to try something that often appears inferior in the store. On the other hand, suppliers recognize the importance of high-quality organic produce to retailers, so are able to charge premiums far above production cost. Nonetheless, our results also show that the market power enjoyed by suppliers is indeed eroding over time as new supply, from both domestic and foreign sources, comes on the market. Although the rapid growth in organic apple sales, and the high cost of establishing organic status ensure that domestic supply will not adjust immediately to meet all of the demand, organic and non-organic margins appear to be converging.

[table 4 in here]

With the estimates in table 4, we can also calculate the implied transfer between the retailer and the supplier under the estimated deviations from the assumed pricing game. Essentially, the rule developed in (17) and (18) implies that the total margin (difference between retail price and production cost) is shared between the retailer and supplier according to the deviation parameters, φ and θ. From the results in table 4, the retail and supplier deviation parameters for non-organic apples imply that retailers earn 75.3% of the total margin, while suppliers earn the remainder, or 24.7%. However, calculating the same set of parameters for retailers and suppliers for organic products (in the base period where $t = 0$) implies that retailers earn only 7.4% while suppliers earn 92.6%. For all varieties, the retail margin is higher for non-organics relative to organics, but the supplier margin is higher for organics in every case.

Moreover, consistent with the results shown in table 4, the supplier margin is significantly higher (in an absolute sense) for organics. Depending on the investment required to obtain organic certification, therefore, we would expect the incentives for suppliers of organic products to be such that the supply will continue to rise rapidly over time. Currently, however, the balance of power clearly still lies with organic apple growers.

[table 5 in here]

The implications of these results are far-reaching for producers of organic products, and those who grow non-organics and may be considering the shift to organics. Any financial decision to gain organic certification must be supported by accurate net-present-value analysis. Therefore, the results shown here may be used to forecast future margins under both a move to organics and the *status quo* for a non-organic grower. While organic production may appear to be attractive, it will be less so in the future. More generally, our results provide a clear demonstration of the incentives importers have to bring in organic products from other countries, with the attendant food safety and invasive species risk that doing so implies. Our findings are also consistent with the dynamics of entry in any industry subject to a new technology. First-entrants are likely to earn the greatest rents, while latecomers can expect to earn only competitive margins. For agricultural products, we show that much of this early rent and first-mover advantage is due to bargaining power in a vertical market structure.

Conclusions

Organics represent an important development in food and agricultural product markets.

Consumer demand for products perceived as free of chemicals or contaminants, more protective of the environment and supportive of local growers – whether or not these are true – has created an entire new class of products in categories ranging from dairy to produce to meat and beyond. Further growth in the supply of organic products, however, depends on the profits available to growers to do so. Forecasting future profit growth in a vertical agricultural market, however, depends critically on how the margin between retail prices and production costs is allocated between the grower (or supplier more generally) and the retailer. In this study, we estimate how this margin is allocated in the U.S. apple market.

Our econometric model consists of a structural (demand and pricing) description of the organic and non-organic U.S. apple markets. The demand model consists of a random-parameters GEV model in which consumers are assumed to make discrete choices between organic and non-organic versions of six major apple varieties. We estimate the GEV model using retail data from five major U.S. metropolitan markets. Given the relative shortage of organic produce described in the media and by produce industry members, our hypothesis is that organic growers enjoy more market power with retail buyers than do non-organic growers. Our findings suggest that retailers earn a greater share of the total margin for non-organic apples, but the allocation of rents shifts toward suppliers of organic apples. Most importantly, perhaps, the proportion of the margin earned by organic suppliers is falling over time. Consequently, while an investment in organic certification may seem lucrative now, it may not be as attractive in the future. With the continuing growth in organic demand, therefore, margins for organic suppliers will remain relatively high, but will erode over time.

Future research in this area would benefit by considering a wider variety of products, and retail data from a greater number of markets. While we consider only apples, organics are also important in dairy, meat and other types of produce. The nature of the decision to enter the organic market is the same in each, but the margin dynamics are likely to be unique. Further, it would also be of interest to more closely examine the role of imported organic products in a model similar to the one used here. Given the relatively weak constraints placed on imported organic food products, some of the market power attributed to domestic growers described in this article is likely eroded by imported produce. With the high margins available in U.S. organic markets and the theoretical insights of Giannakas (2002), how much of this imported produce is truly organic is a matter of some debate.

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Table 1. Organic Retail Price / Retail-Farm Price-Spread Premiums by Variety and Market: 2006 - 2007

	Atlanta		Chicago		Dallas		Los Angeles		New York	
	Price	Spread	Price	Spread	Price	Spread	Price	Spread	Price	Spread
Organic Braeburn[a]	2.102	1.464	1.795	1.157	2.099	1.462	2.174	1.536	2.113	1.475
Regular Braeburn	1.522	1.087	1.359	0.924	1.488	1.053	1.317	0.882	1.535	1.100
	38.1%	34.7%	32.0%	25.2%	41.1%	38.8%	65.0%	74.2%	37.6%	34.0%
Organic Fuji	1.318	0.594	1.562	0.837	2.056	1.331	1.627	0.902	2.216	1.492
Regular Fuji	1.712	1.209	1.358	0.855	1.574	1.071	1.424	0.920	1.606	1.103
	-23.0%	-50.9%	15.0%	-2.1%	30.6%	24.3%	14.3%	-2.0%	38.0%	35.2%
Organic Gala	2.253	1.601	2.033	1.381	1.918	1.266	2.191	1.539	2.034	1.382
Regular Gala	1.354	0.919	1.343	0.909	1.434	1.000	1.212	0.778	1.391	0.957
	66.4%	74.1%	51.4%	52.0%	33.7%	26.6%	80.7%	97.9%	46.2%	44.5%
Organic Golden Del.	1.753	1.133	1.793	1.173	2.001	1.381	1.795	1.175	1.922	1.302
Regular Golden Del.	1.475	1.053	1.232	0.811	1.463	1.041	1.361	0.939	1.428	1.006
	18.9%	7.6%	45.5%	44.7%	36.8%	32.7%	31.9%	25.1%	34.7%	29.5%
Organic Granny Smith	1.944	1.329	1.795	1.179	1.795	1.179	2.009	1.393	1.996	1.381
Regular Granny Smith	1.443	1.028	1.227	0.812	1.438	1.023	1.340	0.924	1.364	0.948
	34.7%	29.3%	46.3%	45.3%	24.8%	15.3%	50.0%	50.8%	46.4%	45.6%
Organic Red Delicious	1.737	1.206	1.652	1.121	1.756	1.225	1.637	1.106	1.759	1.228
Regular Red Del.	1.239	0.870	1.046	0.678	1.153	0.784	1.081	0.712	1.146	0.778
	40.3%	38.6%	57.9%	65.4%	52.4%	56.2%	51.5%	55.3%	53.5%	57.9%

[a] Source: Fresh Look Marketing, Chicago, Il. and Washington Growers Cleaning House, Wenatchee, WA. The spread is calculated as the difference between the average retail price per week and the average PHD price in Washington state.

Table 2. Random Parameter / Nested Logit Demand Estimates

	Random Parameter Nested Logit		Least Squares	
Variable	**Estimate**	**t-ratio**	**Estimate**	**t-ratio**
Discount[a]	0.225*	2.253	0.278*	4.811
Discount*Price	-0.123*	-2.085	-0.143*	-3.475
Time	0.002*	25.688	0.001*	11.901
Atlanta	-0.763*	-73.386	-0.759*	-58.395
Chicago	-0.455*	-50.586	-0.457*	-32.922
Dallas	-0.590*	-49.832	-0.586*	-44.702
Los Angeles	0.569*	75.517	0.562*	41.511
Organic Braeburn	-0.859*	-8.116	-0.83*	-24.473
Organic Fuji	-0.461*	-4.579	-0.436*	-16.318
Organic Gala	-0.416*	-4.297	-0.391*	-13.421
Organic Golden Del.	-0.685*	-6.740	-0.663*	-21.213
Organic Granny Smith	-0.613*	-5.408	-0.592*	-19.454
Organic Red Del.	-0.543*	-5.618	-0.524*	-18.805
Regular Braeburn	-0.224	-1.802	-0.215*	-9.876
Regular Fuji	-0.074	-0.529	-0.062*	-2.921
Regular Gala	-0.049	-0.414	-0.046*	-2.308
Regular Golden Del.	-0.118	-0.681	-0.108*	-5.237
Regular Granny Smith	-0.021	-0.116	-0.012	-0.622
First Quarter	0.158*	16.483	0.025*	2.114
Second Quarter	-0.073*	-7.011	-0.265*	-22.569
Third Quarter	-0.309*	-33.216	-0.517*	-43.883
σ_J	0.850*	240.401	0.851*	188.879
Means of Random Parameters				
Price	-0.365*	-11.268	-0.246*	-13.302
Constant	-0.440*	-4.432	-0.291*	-10.544
Standard Deviations of Random Parameters				
Price	0.099*	43.475		
Constant	0.120*	28.942		
Determinants of Random Parameter Means				
Price (Age)	0.001*	3.441		
Price (Education)	0.008*	5.960		
Constant (Age)	-0.001	-1.456		
Constant (Education)	-0.005*	-2.245		
Variance Parameter				
Sigma	0.339*	307.158		

LLF	-503.369	-4524.6
Chi-Square	21,129.431	17,108.2

[a] A single asterisk indicates significance at a 5.0% level. Estimates are obtained using simulated maximum likelihood with 50 Halton-sequence draws.

Table 2a. Own and Cross-Price Elasticity Matrix: Atlanta Market, RPNL Model

	Elasticity of Row with Respect to Column:											
	Organic Varieties						Non-Organic Varieties					
	Braeburn	Fuji	Gala	Golden Delicious	Granny Smith	Red Delicious	Braeburn	Fuji	Gala	Golden Delicious	Granny Smith	Red Delicious
O. Braeburn	-2.248	0.054	0.017	0.005	0.006	0.009	0.116	0.238	0.293	0.257	0.403	0.588
O. Fuji	0.002	-2.150	0.017	0.005	0.006	0.009	0.113	0.233	0.287	0.251	0.395	0.575
O. Gala	0.003	0.069	-2.841	0.007	0.008	0.012	0.147	0.303	0.372	0.327	0.513	0.748
O. Golden Del.	0.019	0.017	0.007	-2.524	0.130	0.268	0.329	0.289	0.453	0.661	0.432	0.691
O. Granny Smith	0.002	0.063	0.020	0.006	-2.615	0.011	0.135	0.278	0.341	0.299	0.470	0.685
O. Red Del.	0.002	0.049	0.015	0.005	0.006	-2.021	0.104	0.215	0.264	0.232	0.363	0.530
R. Braeburn	0.003	0.069	0.022	0.007	0.008	0.012	-2.714	0.303	0.372	0.326	0.512	0.747
R. Fuji	0.003	0.078	0.024	0.007	0.009	0.013	0.167	-2.896	0.421	0.370	0.580	0.846
R. Gala	0.003	0.068	0.021	0.006	0.008	0.011	0.145	0.299	-2.454	0.322	0.505	0.737
R. Golden Del.	0.003	0.074	0.023	0.007	0.009	0.012	0.159	0.328	0.403	-2.743	0.555	0.809
R. Granny Smith	0.003	0.071	0.022	0.007	0.008	0.012	0.152	0.312	0.384	0.337	-2.422	0.770
R. Red Del.	0.002	0.053	0.017	0.005	0.006	0.009	0.113	0.233	0.286	0.251	0.394	-1.625

[a] Own-price elasticities are calculated using the equation: $\eta_{jj} = (\bar{p}_j(\alpha_{ij} + \beta_{1j} d_j)/(1-\sigma_J))[1 - \sigma_J \bar{s}_{j|J} + (1-\sigma_J)\bar{s}_j]$,
and cross-price elasticities using: $\eta_{jk} = (\bar{p}_j(\alpha_{ij} + \beta_{1j} d_j)/(1-\sigma_J))[-\sigma_J \bar{s}_{k|J} + (1-\sigma_J)\bar{s}_k]$,
where β_{1j} is the discount/price interaction parameter and prices, shares and conditional shares are evaluated at group (market and product) means. Non-IIA substitution is generated through the individual-specific price-response parameter, α_{ij}.

Table 3. Retail Margin Model: Least Squares and GMM

	Least Squares		GMM	
	Estimate	t-ratio	Estimate	t-ratio
Grocery Wages[a]	13.712*	23.555	10.196*	19.756
Retail Mgmt Wages	-0.964*	-11.476	-0.596*	-5.962
Electricity	0.361*	4.538	0.215*	2.521
Retail Margin	0.037*	3.096	0.164*	5.575
Retail Margin * Organic	-0.105*	-4.253	-0.563*	-9.066
Retail Margin * Organic * Time	0.001	1.654	0.001	1.546
Organic Braeburn	-2.542*	-15.383	-1.958*	-12.032
Organic Fuji	-2.927*	-17.733	-2.395*	-14.812
Organic Gala	-2.525*	-15.296	-2.062*	-12.812
Organic Golden Delicious	-2.725*	-16.507	-2.163*	-13.318
Organic Granny Smith	-2.666*	-16.148	-2.106*	-12.989
Organic Red Delicious	-2.782*	-16.847	-2.231*	-13.777
Regular Braeburn	-2.921*	-17.693	-2.188*	-13.243
Regular Fuji	-2.898*	-17.557	-2.142*	-12.934
Regular Gala	-3.016*	-18.279	-2.253*	-13.616
Regular Golden Delicious	-2.959*	-17.938	-2.211*	-13.365
Regular Granny Smith	-2.983*	-18.069	-2.243*	-13.542
Regular Red Delicious	-3.164*	-19.177	-2.441*	-14.812
LLF	-304.619			
G			18.009	
χ^2	5,034.991			

[a] A single asterisk indicates significance at a 5.0% level. The chi-square statistic is a LR ratio test for the least squares model and a quasi-likelihood ratio test for the GMM model.

Table 4. Retail and Wholesale Margin Model: GMM Estimates

Retail Model			Wholesale Model		
Variable	**Estimate**	**t-ratio**	**Variable**	**Estimate**	**t-ratio**
Grocery Wages[a]	9.945*	17.909	**Ag. Chemicals**	-0.060	-0.894
Retail Mgmt Wages	-0.637*	-6.228	**Fuel**	-0.144*	-3.880
Electricity	0.168*	1.989	**Ag. Services**	14.803*	31.051
Retail Margin	0.495*	17.391	**Wholesale Margin**	0.078*	2.108
Ret. Margin * Organic	-0.451*	-7.960	**Whls. Margin * Organic**	1.137*	6.414
Ret. Margin * Organic * Time	-0.001	-0.514	**Whls. Margin * Organic * Time**	-0.012*	-11.233
O. Braeburn	-1.486*	-9.156	**O. Braeburn**	-1.511*	-23.524
O. Fuji	-1.952*	-12.065	**O. Fuji**	-1.406*	-21.839
O. Gala	-1.681*	-10.420	**O. Gala**	-1.447*	-22.576
O. Granny Smith	-1.767*	-10.887	**O. Granny Smith**	-1.477*	-22.985
O. Golden Delicious	-1.696*	-10.463	**O. Golden Delicious**	-1.488*	-23.217
O. Red Delicious	-1.826*	-11.276	**O. Red Delicious**	-1.575*	-24.237
R. Braeburn	-1.815*	-11.114	**R. Braeburn**	-1.686*	-27.015
R. Fuji	-1.738*	-10.621	**R. Fuji**	-1.659*	-26.408
R. Gala	-1.880*	-11.500	**R. Gala**	-1.692*	-27.003
R. Granny Smith	-1.846*	-11.293	**R. Granny Smith**	-1.729*	-27.526
R. Golden Delicious	-1.892*	-11.582	**R. Golden Delicious**	-1.751*	-27.602
R. Red Delicious	-2.067*	-12.692	**R. Red Delicious**	-1.738*	-27.728
$\hat{\varphi}$ **(Organic)**	0.056		$\hat{\theta}$ **(Organic)**	1.216	
$\hat{\varphi}$ **(Regular)**	0.395		$\hat{\theta}$ **(Regular)**	0.078	
G	32.657				
χ^2	1,379.064				
R^2	0.349			0.712	

[a] A single asterisk indicates significance at a 5.0% level. The parameters $\hat{\varphi}$ and $\hat{\theta}$ are fitted values for the retail and supplier conduct parameters, respectively. The chi-square statistic is a quasi-likelihood ratio (QLR) test of the maintained GMM model against a null alternative.

Table 5. Implied Retail and Wholesale Margins

		Organic		Regular	
		Mean	**Std. Dev.**	**Mean**	**Std. Dev.**
Braeburn[a]	**Retail**	0.041	0.017	0.190	0.079
	Wholesale	0.419	0.102	0.018	0.007
Fuji	**Retail**	0.032	0.023	0.184	0.087
	Wholesale	0.462	0.158	0.022	0.007
Gala	**Retail**	0.047	0.019	0.165	0.076
	Wholesale	0.398	0.111	0.018	0.004
Golden Del.	**Retail**	0.038	0.013	0.181	0.061
	Wholesale	0.377	0.117	0.019	0.006
Granny Smith	**Retail**	0.039	0.017	0.181	0.054
	Wholesale	0.378	0.080	0.019	0.003
Red Del.	**Retail**	0.037	0.013	0.144	0.061
	Wholesale	0.328	0.068	0.015	0.003

[a] Margins are estimated using equations (17) and (18) under the maintained model of wholesale Stackelberg leadership. All margins are in cents per pound calculated at the base period (t = 0).