Market Power and Asymmetry in Farm-Retail Price Transmission

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Abstract

A finite mixture model is used to examine whether price asymmetries exist in U.S. fresh strawberry markets. Two distinct pricing regimes are identified. Results show that price asymmetries exist only at 34 percent of the cases and market power has played an important role in generating such asymmetric price relationships.

Market Power and Asymmetry in Farm-Retail Price Transmission

This study examines the farm-retail price transmission process of a produce industry that may be operating in an imperfectly competitive market. A new farm- retail price transmission model is developed and applied to the U.S. strawberry industry. Fresh produce commodities differ from other products in two important aspects. First, most fresh market goods such as lettuce and strawberries are perishable and thus are unstoreable. Second, the short run supply function of these products is inelastic because total production acreage is fixed by the decisions made in the past - months in advance for lettuce and strawberries or years in advance for stone fruits.

These twin characteristics of fresh produce in conjunction with widely fluctuating yield patterns may create multiple pricing regimes. For example, in the case of California iceberg lettuce, Sexton and Zhang observed two distinct price regimes. In particular, they witness that at times when grower price is higher than its harvesting costs, a positive surplus (scarcity rent) exists in the market which is allocated between buyer-retailers and grower-shippers based on their relative bargaining power. Although the case of iceberg lettuce differs from strawberries in many ways, Sexton and Zhang's observation that more than one pricing regime may exist in fresh commodity markets and a buyer-retailer's ability to influence farm price is an increasing function of total shipments recognizes some of the important features of fresh produce industry.

We argue that a monopsonist may be able to influence market prices asymmetrically during a peak harvesting season, when supply is usually higher than normal, but his ability to do so will decline as supply starts to dwindle. Thus, even if the market structure remains the same over time, the pricing behavior of a monopsonist's changes as the total supply swings through its regular seasonal cycles. Recognizing these unique features of fresh produce commodities, we develop a two regime pricing model for fresh market strawberries. A statistical procedure known as a finite mixture model is used to estimate parameters associated with these two regimes.

The empirical testing procedure begins with a seasonal unit roots test to examines whether monthly price series are stationary and is followed by a lag length test to determine the response of retail prices to changes in farm prices. Based on these test results, a model with twelve period lags is used to examine the direction of causality between prices and to estimate farm-retail price transmission functions using a finite mixture model. The mixture parameters are compared with the results obtained from a conventional single equation model and the issue of price asymmetry is examined within as well as between the pricing regimes.

Relevant Studies

In a competitive industry, price changes between farm and retail levels are expected to be symmetric. Nonetheless, many studies report that the farm-retail price transmission process is asymmetric. These studies show that factors such as government intervention (Kinnucan and Forker), differential impacts of demand and supply shifters (Gardner), and concentration in the market levels beyond farm gate (Bernard and Willet) may cause farm-retail price spread to be asymmetric. The recent trend in retail concentration has raised the concern whether the middlemen (wholesaler/retailer) are exercising market power to influence prices asymmetrically (Powers).

Ward examined the relationships among farm, wholesale, and retail prices for fresh vegetables and found that wholesale price leads both retail and shipping point prices. Moreover, he observed that wholesalers are able to influence both retail as well as grower prices asymmetrically. Powers examined the price transmission process for iceberg lettuce industry and also found asymmetry in farm and retail price changes. Most of these studies, however, focus on long term relationship between retail and farm prices and thus, are not able to detect short-term effects which are important for fresh produce industry. Recent studies show that pricing behavior of fresh produce commodities may consist more than on regime. In the case of California iceberg lettuce, Sexton and Zhang observed two distinct pricing regimes. In particular, their argument that the scarcity rent, which exists when grower price is higher than harvesting costs, is allocated between growers and buyers based on their relative bargaining power seems to be more plausible scenario for an industry that deals with perishable and unstoreable products. Following Sexton and Zhang, we define buyer-retailer's ability to influence market prices as a function of total shipments and used this latent variable to segment their pricing behavior into two pricing regimes.

Theoretical Framework

Consider the fresh strawberry marketing industry as a firm which produces a homogenous product (q) using a farm input (x) along with other marketing inputs (m) and sells the product in a competitive market at a price p. The market for non-farm inputs such as labor, electricity, transportation, etc. is likely to be competitive because the share of the industry is much smaller than the overall size of the market. However, an individual firm may enjoy market power in a regional farm input market or in national output market.

Assuming that the marketing cost function is separable between farm and marketing inputs and the relationship between agricultural input and output is one of fixed proportions (i.e., $q = \lambda x$, λ=1) the profit function (π) of the ith marketer/retailer in the jth region can be expressed as

$$\pi_{ij} = pq_{ij} - w_i(Q_j, z)q_{ij} - c_{ij}(q_{ij}, v) \qquad [1]$$

where q_{ij} is the firm's input as well as output quantity, $w_j(Q_j, z)$ is the farm input price in region j, $\Sigma q_{ij} = Q_j$ is the total farm input supply in region j, z is a vector of supply shifting exogenous variables, v is a vector of prices for non-agricultural inputs, and $c_{ij}(q_{ij}, v)$ is the processing cost function of the ith firm in the jth region. The first order condition for firm's profit maximization is

$$\frac{\partial \pi_{ij}}{\partial q_{ij}} = (p - w_j) - \frac{\partial w_j}{\partial Q_j}\frac{\partial Q_j}{\partial q_{ij}} q_{ij} - c_{ij} = 0 \qquad [2]$$

Converting (2) to elasticities, the retail price can be expressed as

$$p = w_j + \theta_{ij}(\varepsilon_j^{-1} Q) + c_{ij} \qquad [3]$$

where $\theta_{ij} = (\partial Q_j / \partial q_{ij})(q_{ij} / Q_j)$ is the regional input market conjectural elasticity of firm i in region j, $\varepsilon_j = (\partial Q_j / \partial w_j)(Q / Q_j)$ is the slope of input supply function in region j times the inverse of region j's national market share, $Q=\Sigma Q_j$ is the total national input/output quantity, and c_{ij} is the marginal processing cost of firm i in region j. Assuming that the slope of input supply function is constant within as well as across the regions (i.e., $\varepsilon_j = \varepsilon$), multiplying equation [3] by q_{ij}, summing over all firms within the region and over all regions, and dividing by Q the aggregate price relationship for the industry as a whole can be derived as (Schroeter and Azzam)

$$p = (w + c) + \theta(\varepsilon^{-1} Q). \qquad [4]$$

Equation [4] shows the optimal behavior of a firm with monopsony power in agricultural input market but faces competitive output and other non-agricultural input markets. The conjectural elasticity parameter (θ) measures the extent of monopsony power exercised by the firm.

However, when the farm input market is perfectly competitive, the conjectural elasticity parameter reduces to zero and the farm-retail price relationship would become $p = w + c$.

The short run pricing model of strawberries, however, would differ from its long-run counterpart because fresh berries are perishable and unstoreable. Moreover, the strawberry supply function becomes inelastic in the short run because production acreage is fixed by the decisions made in the past (months in advance in California and about a year in Oregon). Because of these unique features, berry prices are likely to be renegotiated at each trading period as demand and supply conditions change. In addition, berry production is seasonal as are most other agricultural commodities.

These unique features of fresh produce commodities give rise to multiple regimes of price determination. Sexton and Zhang observed two distinct pricing regimes of California iceberg lettuce - one that clusters around the harvesting costs and the other that lies above it. In the second regime, where the farm price is higher than harvesting costs, a positive surplus exists in the market. Sexton and Zhang argue that this rent is allocated between buyers and sellers based on their relative bargaining power. Moreover, they articulate that the bargaining power of a produce buyer is an increasing function of total shipments.

If a buyer's ability to influence grower prices is a positive function of total shipments, then we would observe two different pricing regimes - one pertaining to the peak harvesting season, when supply is usually higher than normal, and the other associated with an average or below average production periods. In other words, a produce buyer who enjoys monopsony power in farm input market would be better able to influence prices at times when domestic production peaks rather than at periods when it is dwindling. Under these assumptions, the farm retail price relationship would consists of two distinct regimes

$$p_{peak} = \beta^{w}_{peak} w + \beta^{c}_{peak} c + \theta_{peak} (\varepsilon^{-1} Q)$$
$$p_{off} = \beta^{w}_{off} w + \beta^{c}_{off} c + \theta_{off} (\varepsilon^{-1} Q). \qquad [5]$$

This conceptualization of fresh produce industry allows both farm-retail price relationship as well as the market power parameter to vary across the regime. In other words, a monopsonist is allowed to switch between competitive and monopsonistic behavior as the input supply swings through its seasonal cycles.

Empirical Model and Data

Assuming that buyer-retailer's ability to influence prices is a monotonically increasing function of total shipments of fresh strawberries (Q), the relationship between shipments and buyer ability can be expressed as

$$\pi = f(Q) \qquad {}^{\partial\pi}\!/_{\partial Q} > 0 \qquad [6]$$

where π measures buyer-retailer's ability to influence farm prices, which takes a value between zero and one. At each trading period a buyer makes his pricing decision - whether to offer a competitive or a monopsonist price. Since the pricing decisions are discrete, there should be some threshold level which separates prices between monopsonistic and vice versa. Once the market power and the threshold level are known, the pricing regimes can be identified as

$$\boldsymbol{P} = \begin{cases} \text{Regime}-1 & \textbf{\textit{if}} \quad \pi < c \\ \text{Regime}-2 & \textbf{\textit{Otherwise}} \end{cases} \qquad [7]$$

Thus, in an empirical setting, if π and c are known a priori then the sample can be segmented into two sub-samples and the parameters associated with these two regimes can be estimated separately. However, both of these values are not known. A statistical procedure known as a finite mixture estimation procedure can be used to address this estimation problem (see Titterington, et al. for excellent discussion).

We used expectation maximization algorithm (EM) to estimate both an optimal mixing weight (π) as well as the parameters associated with each regimes iteratively. This approach is capable of inferring an optimal mixing weight from the data that defines two distinct regimes, which are relatively homogenous within the group but differ significantly across the groups. The EM algorithm has been widely used in estimating missing data models (see Dempster, et al., Caudill, et al., Caudill and Acharya details on estimation procedure). In general, a finite mixture distribution of a price can be expressed as

$$f_i(P_i) = \pi_1 f_{i1}(P_i) + \pi_2 f_{i2}(P_i) + \ldots + \pi_k f_{ik}(P_k) \qquad [8]$$

where $\pi_j > 0$, $\sum\pi_j=1$, $f_j>0$, and $\int f_j(m_j)dm = 1$. Thus, the mixture density function is a probabilistically weighted average of component densities (f_j). Assuming that fresh strawberry prices are normally distributed, a two regime pricing model can be expressed as

$$f_i(P_i|\theta) = \pi\phi_1(P_i|\mu_1,\sigma_1) + (1-\pi)\phi_2(P_i|\mu_2,\sigma_2) \qquad [9]$$

were φ_j, are the normal density functions and $\mu_j = \mathbf{X\beta}$ are vectors of explanatory variables and respective parameters. Using this framework, the two regime strawberry pricing model defined in equation [5] can be expressed as

$$P = \begin{cases} \beta_{11}w + \beta_{12}c + \theta_1(\varepsilon^{-1}Q) + \varepsilon_1 & \text{for peak-season} \\ \beta_{21}w + \beta_{22}c + \theta_2(\varepsilon^{-1}Q) + \varepsilon_2 & \text{for off-season} \end{cases} \qquad [10]$$

were ε_j are normally distributed i.i.d. error terms. The cost function, C, is defined as Diewert's Generalized Leontief due to its several desirable properties such as: it is homogeneous in prices without normalization, it is affine in output without further restrictions, and it imposes convexity in output. While properties such as concavity in prices, symmetry, and monotonicity can be maintained and tested. For a single output (Q) and n input prices (x_i), the Generalized Leontief cost function can be specified as

$$C(q,v) = q\sum_i \sum_j \gamma_{ij}(v_i v_j)^{1/2} + q^2 \sum_i \gamma_i v_i + \varepsilon$$

where ε is a random error term, and the set of input prices include labor wages, unit price of electricity and fuel for food processing industry. Given this cost function, derivation of a marginal cost function is straightforward.

To match the theoretical model with empirical observations, various statistical procedure are followed. First, a unit roots test was carried out to examine whether monthly farm retail prices are stationary at seasonal frequencies. Second, Akaike's information criterion was used to determine the lag lengths and a model with twelve lags is selected. Third, the selected model was used to examine the causality between prices as proposed by Geweke, Meese, and Dent, which is based on Sims' test. Results show that farm prices cause retail prices but not the other way around. Based on these empirical test and the theoretical relationship derived in equation [10], the farm to retail price transmission process for fresh strawberry marketing industry was specified as

$$
P = \begin{cases} \alpha_1 + \sum_{i=0}^{12} \beta_{1i}^{+} \Delta FP_{t-i}^{+} + \sum_{i=0}^{12} \beta_{1i}^{-} \Delta FP_{t-i}^{-} + \beta_1^c c + \theta_1 (\varepsilon^{-1} Q) + \varepsilon_1 \\ \alpha_2 + \sum_{i=0}^{12} \beta_{2i}^{+} \Delta FP_{t-i}^{+} + \sum_{i=0}^{12} \beta_{2i}^{-} \Delta FP_{t-i}^{-} + \beta_2^c c + \theta_2 (\varepsilon^{-1} Q) + \varepsilon_2 \end{cases}
$$

$$
\Delta FP_t^{+} = \sum_{t=1}^{T} \max(FP_t - FP_{t-1}, 0) \text{ and}
$$

$$
\Delta FP_t^{-} = \sum_{t=1}^{T} \min(FP_t - FP_{t-1}, 0). \qquad [11]
$$

where superscripts + and - denote cumulative value of rising and falling farm prices which are computed via the Wolffram methodology as modified by Houck. Thus, a formal test of the hypothesis that the farm-retail price transmission mechanism in fresh market strawberry market is symmetric would be

$$
\begin{aligned} &H_N : \sum_{i=0}^{12} \beta_{ji}^{+} = \sum_{i=0}^{12} \beta_{ji}^{-} \qquad \text{for j = peak and off-season.} \qquad [12] \\ &H_A : H_N \quad \textit{not true} \end{aligned}
$$

The hypothesis test [12] is a test of linear restriction and a t-test is appropriate. To test whether a single regime or a two regime model fits the data better, a corrected log likelihood ratio test as suggested by Wolfe was used. Although it is not a formal specification test, the simple t-test on mixing weight parameter (π) can also be used to test the significance of two regime model.

Equation [11] is estimated using monthly data from January 1980 to December 1998. Retail price and non-market input cost data were obtained from the BLS web site and shipments and shipping point prices were downloading from the USDA web site. With these data, the model was estimated sequentially. In the first stage, the inverse elasticity of fresh strawberry is obtained.

Then, the fitted values of this variable are then used in the second stage finite mixture model. The estimate of the second stage are found using the iterative maximum likelihood method. All econometric procedures converged quickly and parameter estimates were stable over a range of starting values.

Empirical Results

We begin the empirical analysis by testing for unit roots followed by a lag length test to determine the response of retail prices to changes in farm prices. Based on the results, a model with appropriate lag lengths is used to examine the direction of causality between prices, and then to address the issue of price asymmetry.

Unit root test results show that both farm as well as retail strawberry prices are stationary at seasonal frequencies (test results on unit roots, lag lengths, and causality are available on request from author). A model with twelve lags is selected based on the Akaike Information Criteria and is used for causality tests. Results show that farm prices cause retail price but not other way around. Then, a model with twelve lags for both falling and rising farm prices is used to test for farm-retail price asymmetry in fresh strawberry market. The finite mixture parameters along with results from the conventional one regime model are reported in Table 1.

A corrected log likelihood ratio test, which is generally known as the Wolfe's test in finite mixture literature, was used to check for the significance of two regime against a single regime model. The Wolfe's test statistics (239.16) is significant at 1 percent level meaning that a two regime mixture model outperforms a single regime model.

The parameter measuring the mixing weight, $\pi = 0.66$, is also highly significant implying that there are two price regimes with 66 percent of the observations falling in the first regime and the remaining 34 percent in the second regime. One of most distinguishing feature between these two regimes is that the parameter measuring market power, θ is not significant in the first regime, while it is highly significant in the second one. Thus, other things remaining the same, one would expect a symmetric price response in the first regime. While the relationship in the second regime can be expected to asymmetric because the coefficient measuring the market power is small but highly significant.

The farm-retail price response parameters for short and long run are summarized in Table 2. The rising and falling farm price response parameters are not significantly different in the short-run. The significant difference in the sum of the coefficients of the rising-vis-a-vis- falling farm price variables in the OLS model, however, shows that the existence of market power, even though it may be weak, may cause price asymmetries to persist in the long run. A contrasting picture is depicted by results from the two different regimes of the model.

The results from regime-1 show that the response of retail price to the changes in cumulative sums of rising and falling farm prices is not significantly different in both short-run as well as long-run. Moreover, the market power parameter is not significantly different from zero implying that strawberry price was set at a competitive level in about 66 percent of the cases. These results - absence of market power as well as price asymmetry in regime-1 - supports the hypothesis that in a competitive industry, price changes between farm and retail levels are symmetric.

On the other hand, results from the second regime show a different picture. In this case, price asymmetry as well as market power exists in 34 percent of the cases. Moreover, the response of fresh strawberry retail price to rising farm prices is significantly higher than its response to falling prices both in short and long run. These results show that because fresh strawberry buyer-retailers enjoy market power in the strawberry market in about one third of the times this may have caused price changes between farm and retail levels to be asymmetric.

Conclusions and Implications

The objectives of this study are to determine whether asymmetries exist in a fresh produce industry which may be operating in an imperfectly competitive market. The fresh commodity market is unique in the sense that its products are perishable and the short run supply function is inelastic. These unique features of the industry may generate multiple regimes of price determination. We develop a farm- retail price transmission model with two pricing regimes and used to test for existence of market power and price asymmetries.

Empirical results show that two distinct price regimes exist in the fresh strawberry market - one that operates during the peak harvesting season and the other that operates during off-season. In other words, produce buyers change their pricing behavior as the production season changes. During the peak harvesting seasons, they are able to exert some influence on farm prices (34 percent of the cases), however, their ability to do so declines as the season matures. As expected, the downward pressure on prices is critical particularly during the months of March to May, which is the peak harvesting season for domestic growers. Since both domestic production as well as Mexican imports peak around the same season, export promotion activities conducted around the months of March-May might be more helpful than during other months.

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Table 1: OLS and Mixture Estimators

Variables	OLS		Regime-1		Regime-2	
	Coefficients	Std. Error	Coefficients	Std. Error	Coefficients	Std. Error
Constant	3.3489	17.202	-9.7603	34.423	174.1134 **	2.500
$\Delta^+ FP_t$	0.3279 **	0.137	0.1757	0.281	1.0749 **	0.014
$\Delta^+ FP_{t-1}$	0.5703 **	0.172	0.5217 *	0.306	1.2715 **	0.022
$\Delta^+ FP_{t-2}$	0.1108	0.169	0.3472	0.317	-1.3816 **	0.024
$\Delta^+ FP_{t-3}$	0.0298	0.125	-0.0937	0.193	-0.2589 **	0.016
$\Delta^+ FP_{t-4}$	-0.0215	0.106	0.0469	0.150	0.2704 **	0.010
$\Delta^+ FP_{t-5}$	0.0607	0.093	0.0692	0.289	-0.0313 **	0.007
$\Delta^+ FP_{t-6}$	-0.0401	0.081	-0.0551	0.242	-0.0906 **	0.009
$\Delta^+ FP_{t-7}$	0.1142	0.082	0.0937	0.204	0.1831 **	0.006
$\Delta^+ FP_{t-8}$	0.0218	0.084	0.0043	0.179	-0.3555 **	0.010
$\Delta^+ FP_{t-9}$	0.1012	0.096	0.1098	0.162	0.4814 **	0.012
$\Delta^+ FP_{t-10}$	0.1191	0.096	0.1041	0.154	-0.0044	0.015
$\Delta^+ FP_{t-11}$	0.0512	0.114	-0.0780	0.170	-0.1591 **	0.017
$\Delta^+ FP_{t-12}$	0.0670	0.136	0.1513	0.217	0.4377 **	0.011
$\Delta^- FP_t$	0.4757 **	0.144	0.5154 *	0.266	0.1129 **	0.013
$\Delta^- FP_{t-1}$	0.4657 **	0.115	0.4261 *	0.214	0.4938 **	0.011
$\Delta^- FP_{t-2}$	0.0201	0.106	-0.1204	0.214	0.2677 **	0.007
$\Delta^- FP_{t-3}$	0.0630	0.094	0.2770	0.180	0.1051 **	0.007
$\Delta^- FP_{t-4}$	0.0230	0.091	-0.0313	0.217	-0.0721 **	0.006
$\Delta^- FP_{t-5}$	-0.0719	0.091	-0.0956	0.221	-0.0792 **	0.009
$\Delta^- FP_{t-6}$	-0.0092	0.091	-0.1499	0.206	-0.2126 **	0.007
$\Delta^- FP_{t-7}$	0.0772	0.096	0.1168	0.132	0.1328 **	0.010
$\Delta^- FP_{t-8}$	0.0817	0.108	0.1348	0.196	0.2035 **	0.011
$\Delta^- FP_{t-9}$	0.2289	0.128	0.1000	0.268	-0.1510 **	0.019
$\Delta^- FP_{t-10}$	0.0800	0.175	0.2623	0.374	0.0618 *	0.037
$\Delta^- FP_{t-11}$	0.0927	0.192	0.1503	0.446	-0.0391 *	0.020
$\Delta^- FP_{t-12}$	-0.0637	0.123	-0.1983	0.164	0.4441 **	0.015
Wage (hourly)	0.4656	1.120	-0.7828	2.086	12.1411 **	0.162
Electricity	-0.0686	0.402	-0.2911	0.852	3.6472 **	0.057
Fuel	1.1608	1.673	3.4105	4.834	-8.2576 **	0.105
Wage*Electricity	-0.0682	1.388	1.2130	2.740	-14.3226 **	0.195
Wage*Fuel	-2.6450	3.055	-1.9143	7.882	12.4257 **	0.338
Electricity*Fue1	0.9292	1.344	-0.1613	3.827	-2.9987 **	0.155
$\varepsilon^{-1}Q$	-0.0370 **	0.015	-0.0518	0.034	0.0263 **	0.002
σ_i			0.0782 **	0.002	0.0012 **	0.000
π			0.6561 **	0.043	0.3439 **	0.043
R^2	0.9236					
LL	139.9225		256.7434		256.7434	

**, * denote significant at 1 and 5 percent levels, respectively.

Table 2. Farm-Retail Price Response Parameters

Models	Short-run				Long-run			
	Rising	Falling	Difference	t-value	Rising	Falling	Difference	t-value
OLS	0.328	0.476	-0.148	-0.71	1.513	1.463	0.049 *	2.18
Mixture-1	0.176	0.515	-0.340	-0.77	1.397	1.387	0.01	0.00
Mixture-2	1.075	0.113	0.962 **	64.59	1.438	1.269	0.170 **	78.82

Table 3. Farm-Retail Price Transmission Elasticities

	Short-run			Long-run		
Models	Rising	Falling	Difference (%)	Rising	Falling	Difference (%)
OLS	0.214	0.310	-31.071	0.985	0.953	3.369
Mixture-1	0.114	0.336	-65.913	0.910	0.904	0.719
Mixture-2	0.700	0.074	851.713	0.936	0.826	13.398