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Testing for Symmetry in Price Transmission: An Extension of the Shiller Lag Structure with an Application to Fresh Tomatoes

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An empirical model of the price relationship between distribution stages is developed based on the Shiller lag. The assumption of constant returns to scale is relaxed to incorporate changes in the volume of shipments. An iterative GLS methodology is developed to estimate the model. Tests for symmetry, length of adjustment, and the amount of price transmission are outlined. An application using the change in the retail price of tomatoes based on shipping point price changes is described. Results suggest that the supermarket chain does not respond differently to price increases versus decreases at the shipping point level.

Key Words: farm level, price spreads, price transmission, retail level, Shiller lag structure, symmetry, tomatoes

Price spreads between farm and retail levels continue to be a controversial topic. Growers are dissatisfied with their diminished share of the retail food dollar. Middlemen and retailers downstream in the distribution channel, however, argue their margins are justified by the value added. The speed and extent of price responses at one level due to positive and negative price changes at other stages in the market channel provide information about the behavior of price spreads, and therefore can be used to assess pricing efficiency.

Studies of the link between farm and retail levels can be separated into two groups. One focuses on developing theoretical models of pricing behavior (e.g., Azzam, 1999; Gardner, 1975; Holloway, 1991; Wohlgenant, 1989). The second centers on empirical descriptions of price linkages (e.g., Powers, 1994). The analysis described here fits the second category. The Houck (1977) procedure for estimating nonreversible functions has served as the basis for most of these studies. Houck's methodology has been extended and applied across a variety of commodities including fresh produce (e.g., Bernard and Willett, 1996; Hansmire and Willett, 1993; Heien, 1980; Mohamed, Arshad, and Hashim, 1995; Pick, Karrenbrock, and Carman, 1990;

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Powers, 1994; Ward, 1982), dairy products (e.g., Kinnucan and Forker, 1987), and meat products (e.g., Boyd and Brorsen, 1988; Griffith and Piggott, 1994; Herrman, Mittelhammer, and Lin, 1992; Punyawadee, Boyd, and Faminow, 1991).

The dual objectives of our study are to present a new model of price spreads and to illustrate its application. We incorporate a more realistic price adjustment structure to reflect changes in the volume of shipments and a flexible adjustment process on the part of the retailer to changes in upstream prices. These modifications are well suited for fresh produce; its highly perishable nature, coupled with little change in the product from the grower to the consumer, results in price transmissions being a key component of the market channel. The model can be estimated using an iterative generalized least squares (GLS) procedure. Tests for symmetry, length of adjustment, and the amount of price transmission in response to price increases versus decreases can be conducted. Empirical application is illustrated through an analysis of the farm-to-retail price spread for tomatoes.

A Price Linkage Model

An empirical description of the markup model (Heien, 1980) is based on three assumptions. First, retail-level produce is marketed using fixed proportions of the shipping-level commodities and marketing inputs, thus implying Leontief production technology. Second, firms operate under constant returns to scale, implying constant marginal costs. The final assumption of the markup model is that firms operate under competitive market structures. Under these conditions, the retail price (R) in period t can be expressed as:

$$R_{i,t} = b_{1,i}S_{i,t} + b_{2,i}Z_{i,t}, \tag{1}$$

where S is the free-on-board (FOB) shipping point price, Z denotes the marketing costs, and i denotes the ith retail-level commodity. Given equation (1), changes in the retail price to actual or anticipated shifts in supply or demand within the marketing system are due to transportation, storage, packing, grading, etc. Lags in price linkages should therefore equal the amount of time necessary to move the produce from one level to the next; otherwise, price adjustment is inefficient (Powers, 1994).

Support for the first assumption is based on there being limited opportunity to substitute marketing inputs in response to changing factor prices, particularly in the short run. Also, the technology for distributing and marketing produce changes very slowly over time. The second assumption is consistent with fees for cooling, packing, and selling fresh produce remaining constant throughout the year (Powers, 1994). The third assumption is supported by empirical evidence which suggests food retailers behave competitively (Holloway, 1991).

Empirically testing the markup model involves addressing the notions of causality, lags in price response, and asymmetry (Kinnucan and Forker, 1987). Each of these is considered below. Equation (1) implicitly assumes shipping point prices "cause" retail prices. Although methods exist for testing causal direction (e.g., Granger, 1969), Conway et al. (1984) argue that such methods can be misleading and unreliable. Furthermore, previous studies using the markup model to investigate vertical price linkages in fresh produce specified retail prices as functions of price movements at lower market levels (e.g., Mohamed, Arshad, and Hashim, 1995; Pick, Karrenbrock, and Carman, 1990; Powers, 1994; Ward, 1982).

Lags in price response exist for many reasons. The time required to pack, store, and transport products contributes to price responses being less than instantaneous (Kinnucan and Forker, 1987). Second, retailers may be slow to adjust their prices if they consider price changes at lower levels in the marketing channel to be transitory rather than permanent (Powers, 1994). Third, before changing the price of fresh produce commodities, retailers may want to check product availability from alternate sources. For example, if the price of a Washington State red delicious apple changes, a retailer may inquire about possible alternatives, such as local red delicious apples, or those from another state. Other reasons for lagged retail response include costliness of repricing (Heien, 1980) and differences in information use at various exchange points within the marketing system (Ward, 1982) (e.g., adoption of internet technology and efficient consumer response).

The empirical markup model can be modified, as explained below, to accommodate the possibility of different responses in terms of the extent of the change and the amount of adjustment time depending on whether upstream prices are increasing or decreasing. In the short run, retail prices may respond asymmetrically to rising and falling upstream prices under several conditions. Asymmetric response is consistent with theoretical models (e.g., Gardner, 1975) which show that elasticities depend on whether upstream price changes are motivated by a shift in farm supply, marketing input supply, or retail demand. However, these shifts do not explain asymmetrical responsiveness under Leontief marketing technology and perfect elasticity of supply of marketing inputs which, in the short run, are reasonable for supermarket chains (Powers, 1994) and are consistent with the empirical inquiry addressed here. Further, given the assumptions underlying the markup model, retail demand shifts should have little relevance in the short-run price linkage relationship.

Speculative inventories of a commodity may also explain asymmetrical price responses. However, perishability of fresh tomatoes precludes this possibility.[1] Other factors possibly facilitating asymmetric responsiveness include market power (Kinnucan and Forker, 1987; Mohamed, Arshad, and Hashim, 1995; Powers, 1994; Ward, 1982), risk-averse firm behavior under conditions of profit uncertainty (Powers, 1994), strategic pricing which recognizes the price-inelasticity of demand for food products, and prospect theory (Benartzi and Thaler, 1995).

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[1] As shipments increase, the retailer's interest in lowering price to increase the quantity demanded may be associated with price reductions that are larger and/or occur faster than price increases.

Equation (1) can be altered to allow for short- and long-run adjustments, asymmetry, and lags in price response by using the Houck procedure. For the *i*th commodity in period *t*, an empirical analogue to equation (1) is specified as follows:

$$(2)\qquad RP_{i,t} = \sum_{m=0}^{r} \delta_{1,i,m} SPR_{i,t-m} + \sum_{m=0}^{f} \delta_{2,i,m} SPF_{i,t-m} + \sum_{m=0}^{r^*} \delta_{3,i,m} TCR_{i,t-m} + \sum_{m=0}^{f^*} \delta_{4,i,m} TCF_{i,t-m} + e_{i,t},$$

where *RP* is the retail price change from period 0 to period *t*, *SPR* is the sum of all week-to-week increases in the FOB shipping point price from period 0 to period *t*, *SPF* is the sum of all week-to-week decreases in the FOB shipping point price from period 0 to period *t*, *TCR* is the sum of all week-to-week increases in transportation costs from period 0 to period *t*, *TCF* is the sum of all week-to-week decreases in transportation costs from period 0 to period *t*, *r* is the lag length for rising prices, *f* is the lag length for falling prices, r^* is the lag length for rising costs, f^* is the lag length for falling costs, and *e* is a random error term with the traditional assumptions.

The assumption of constant returns can be relaxed, as shown below. In particular, seasonality and product volume can be incorporated into (2) without increased parameterization or fixed seasonal variation across years implied by current approaches (e.g., Lambregts and Capps, 1990). This is accomplished through a variable (*j*) which reflects the volume of shipments. There is some flexibility in shipments (e.g., cold storage and gassing of tomatoes). But such opportunities are limited due to the perishable nature of the commodities and a desire to maximize shelf life at the retail level. Thus, *j* is considered to be independent of the random error in the same period. Once *j* is defined, it can then be incorporated directly into the regression model. The approach used below is to let *j* be the number of millions of boxes shipped per time period. This allows the volume of shipments to be a variable in the price transmission process.

Equation (2), reflecting the information in *j* (the volume of shipments), can be rewritten as:

$$(3)\qquad RP_{i,t} = \sum_{m=0}^{r} \delta_{1,i,m} \left(j * SPR_{i,t-m} \right) + \sum_{m=0}^{f} \delta_{2,i,m} \left(j * SPF_{i,t-m} \right) + \sum_{m=0}^{r^*} \delta_{3,i,m} TCR_{i,t-m} + \sum_{m=0}^{f^*} \delta_{4,i,m} TCF_{i,t-m} + e_{i,t}.$$

Defined in this manner, the effects depend on the volume of shipments, which are, of course, seasonal in nature. Use of the Shiller (1973) procedure with seasonally varying data produces an additional modeling advantage concerning the effects of weather. Requiring a model's seasonal parameters to vary smoothly can be regarded as a way of approximating the average effects of weather on the parameters (Gersovitz and MacKinnon, 1978). Sums of the marginal effects can be expressed as:

$$\sum_{m=0}^{r} \frac{\partial RP_{i,t}}{\partial SPR_{i,t-m}} = \sum_{m=0}^{r} \delta_{1,i,m}(j) \quad \text{and} \quad \sum_{m=0}^{f} \frac{\partial RP_{i,t}}{\partial SPF_{i,t-m}} = \sum_{m=0}^{f} \delta_{2,i,m}(j).$$

Alternatively, the marginal impact of j on $RP_{i,t}$ for any time period t ! m is represented by:

$$\text{(4)} \qquad \frac{\partial RP_{i,t}}{\partial j} = \sum_{m=0}^{r} \delta_{1,i,m} SPR_{i,t-m} + \sum_{m=0}^{f} \delta_{2,i,m} SPF_{i,t-m}.$$

As shown by equation (4), the impact of any particular j must be tracked over the lag periods for rising and falling prices. This allows the seasonal effects to be captured in both rising and falling prices, and their impacts can be distributed over time.

The Shiller approach for incorporating a lag structure into a regression model constrains only the parameter means, rather than the parameters themselves. That is, the estimation technique (described below) estimates the average distributed lag relationship across harvest years. This is a more flexible lag structure compared to prior approaches. In particular, the Almon (1965) distributed lag requires the functional form to hold exactly across the harvest years, i.e., the relationship between the lag weights and the lag is exact. Shiller lags only require the average relationship between weights and the lag to have an explicit functional form. For example, if a geometric lag is used, the Almon approach assumes it holds exactly in every harvest year, whereas the Shiller framework only requires it to hold on average across the harvest years. Therefore, Shiller lags are better representations of prior information (lag structure) (Fomby, 1979; Shiller, 1973; Taylor, 1974).

Using the Shiller model, shipping point price parameters of equation (3) are assumed to lie on a polynomial of degree q (called the degree of smoothness prior) of the form:

$$\delta_{1,i,m} = \alpha_0 + \alpha_1 m + \ldots + \alpha_q m^q, \qquad \delta_{2,i,m} = \alpha_0^* + \alpha_1^* m + \ldots + \alpha_q^* m^q.$$

This is equivalent to estimating (3) subject to sets of linear constraints of the form:

$$\Delta^{q+1}\delta_{1,i,m} = 0, \qquad \Delta^{*q+1}\delta_{2,i,m} = 0,$$

where) is the difference operator (e.g.,)$$_i$ = (1 ! L)$$_i$ = $$_i$! $$_{i!1}$), and the superscript is the amount of differencing. In applying the Shiller procedure, the sets of linear constraints become stochastic such that:

$$\text{(5)} \qquad \Delta^{q+1}\delta_{1,i,m} = w_m, \qquad \Delta^{*q+1}\delta_{2,i,m} = w_m, \qquad w_m \sim N(0, \sigma_w^2).$$

Equation (5) can be rewritten as:

$$\text{(6)} \qquad \mathbf{R}^1\delta_{1,i,m} = w_m, \qquad \mathbf{R}^2\delta_{2,i,m} = w_m, \qquad w_m \sim N(0, \sigma_w^2),$$

where $\mathbf{R}^1$ is a matrix of order {(r ! q), ($r+1$)}, and $\mathbf{R}^2$ is a matrix of order {(f ! q), ($f+1$)}. They can be combined into a single matrix having {(r ! q) + (f ! q)} rows and $\{(r+1) + (f+1)\}$ columns, with **R** denoting a set of restrictions that reflects information specific to the rising and falling segmented variables, respectively.

Applying the Shiller approach to equation (3) has implications regarding the seasonal effects in the model. An interpretation of smoothness priors is that the estimated coefficients can deviate from any polynomial as long as they do so smoothly (Maddala, 1977). This implies the lagged seasonal effects in the model will vary smoothly over time. In cases of plentiful data or steady demand for products at the retail level, this could increase the efficiency of the parameter estimates. Moreover, the inferences concerning short- and long-run adjustments and asymmetry in price response should be better with smoothly varying seasonal effects.

From equation (3), the sums of the $*_{1,i,m}$ and $*_{2,i,m}$ coefficients represent the price transmission process. The time required for the price adjustments to occur are reflected in r and f, and if they are equal, the transmission speeds are the same. A formal test of symmetry in price adjustment can be developed by constructing the following hypothesis:

$$\sum_{m=0}^{r} \delta_{1,i,m} = \sum_{m=0}^{f} \delta_{2,i,m}. \tag{7}$$

This null hypothesis can be assessed using an F-test composed of the sum of squared errors with and without the restriction (7). Also, the speed of adjustment (intra-period) can be tested by the null hypothesis:[2]

$$\delta_{1,i,0} = \delta_{2,i,0},\ \delta_{1,i,1} = \delta_{2,i,1},\ \ldots,\ \delta_{1,i,r} = \delta_{2,i,f}. \tag{8}$$

Similarly, an F-test using the sum of squared errors with and without the restrictions in equation (8) can be used to evaluate each of these equalities (Boyd and Brorsen, 1988).

Estimation of the Coefficients

Although Shiller's original work was presented in a Bayesian format, Taylor (1974) demonstrated the mixed estimation procedure developed by Theil and Goldberger (1961) is a straightforward method of incorporating smoothness priors into the estimation process. The mixed estimation procedure is developed by incorporating stochastic linear restrictions to modify the regression model so that:

$$\begin{bmatrix} \mathbf{Y} \\ \boldsymbol{\lambda} \end{bmatrix} = \begin{bmatrix} \mathbf{X} \\ \mathbf{R} \end{bmatrix} \boldsymbol{\delta} + \begin{bmatrix} \mathbf{u} \\ \mathbf{v} \end{bmatrix}, \tag{9}$$

where **Y** and **u** are $(n \times 1)$ vectors, 8 and **v** are $\{(r \,!\, q) + (f \,!\, q) \times 1\}$ vectors, **X** is a known $\{n \times (r+1) + (f+1)\}$ matrix, **R** is a known $\{(r \,!\, q) + (f \,!\, q) \times (r+1) + (f+1)\}$

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[2] The set of equations also applies when $r \ldots f$. In these instances, the computed values equal zero, where appropriate.

matrix, and ***** is an $\{(r+1) + (f+1) \times 1\}$ vector of regression parameters. Further, it is assumed E[**u**] and E[**v**] = 0, cov[**u**] = $F^2 I$, cov[**v**] = R, and **u** and **v** are independent. Also, it is required that 8 has a nonzero variance. The first set of *n* equations is the linear representation of sample information, while the second set of $\{(r \; ! \; q) + (f \; ! \; q)\}$ equations refers to the prior information that supplements the sample.

The Prior Integrated Mixed Estimator (PIME) developed by Mittelhammer and Conway (1988) expresses the prior information on **R*** in terms of a subjective probability distribution of potential **R*** values with mean vector S and covariance matrix R. The subjective distribution assigned to 8 then represents the perceived relative degrees of belief that the various estimates of the model are correct. The PIME estimator is expressed as:

$$\boldsymbol{\delta}_{PIME} = (\sigma^{-2}\mathbf{X}'\mathbf{X} + \mathbf{R}'\boldsymbol{\psi}^{-1}\mathbf{R})^{-1}(\sigma^{-2}\mathbf{X}'\mathbf{Y} + \mathbf{R}'\boldsymbol{\psi}^{-1}\boldsymbol{\Omega}). \tag{10}$$

The Shiller estimator is defined as:

$$\boldsymbol{\delta}_{S} = (\sigma^{-2}\mathbf{X}'\mathbf{X} + \mathbf{R}'\boldsymbol{\psi}^{-1}\mathbf{R})^{-1}(\sigma^{-2}\mathbf{X}'\mathbf{Y}). \tag{11}$$

If the stochastic restrictions can be assumed to be independent with a common variance n^2, then R = n^2**I**. The estimator given by equation (11) can then be written as follows:

$$\boldsymbol{\delta}_{S} = (\mathbf{X}'\mathbf{X} + k\mathbf{R}'\mathbf{R})^{-1}\mathbf{X}'\mathbf{Y}, \tag{12}$$

with a variance-covariance matrix of:

$$\text{Var-Cov}(\boldsymbol{\delta}_{S}) = \sigma^{2}(\mathbf{X}'\mathbf{X} + k\mathbf{R}'\mathbf{R})^{-1}\mathbf{X}'\mathbf{X}(\mathbf{X}'\mathbf{X} + k\mathbf{R}'\mathbf{R})^{-1}. \tag{13}$$

Based on (11) and (12), *k* is a parameter given by F^2/n^2, where F and n are assumed known. The parameter indicates how confident researchers are with respect to sample versus prior information (Venkateswaran, Kinnucan, and Chang, 1993). In addition to the advantages of using smoothness priors, the Shiller procedure is flexible in that it subsumes the ordinary least squares (OLS) and Almon estimators as special cases. For example, as *k* approaches zero, OLS estimates are obtained. As *k* approaches infinity, Almon estimates for a *q*th-degree polynomial are acquired (Shiller, 1973). Lindley and Smith (1972) suggest a procedure which iteratively estimates *k*. It involves starting with the OLS estimates of the $*_i$ and taking their variance as an estimate of n^2. This is expressed as:

$$\varphi^2 = \left(\frac{1}{(r+1) + (f+1)}\right) \sum_{i=1}^{(r+1)+(f+1)} \left(\delta_i - \delta_i'\right)^2, \tag{14}$$

where *N is the mean of the $*_i$. The new (Shiller) estimates of the $*_i$ are computed using $k = F^2/n^2$, where F^2 is the OLS residual variance. Next, n^2 is revised using the new $*_i$, and the process is repeated until a satisfactory level of convergence is attained (typically when the sum of the absolute values of the changes in the coefficients is less than .001).

Data and Empirical Model

Fresh produce continues to be a major draw for supermarkets. Surveys of food shoppers consistently reveal that high quality produce departments are the first or second most frequently cited reasons for shopping at a supermarket (The Food Institute, 1998). In terms of consumption, tomatoes are the third largest vegetable commodity (potatoes are first, followed by lettuce) at approximately 16 pounds per capita per year. For the 1992–1996 period, the average value of tomatoes for fresh market was \$1.065 billion (The Food Institute, 1998). Tomatoes were selected for an empirical application. In addition, they are highly perishable, and there are seasonal fluctuations throughout the growing periods. Finally, retail-level price data were available.

Weekly price data for shipping point and retail levels were used. Shipping point data were obtained from the Florida Tomato Committee and reflect the average weekly FOB price received by producers for a 25-pound box of tomatoes. The shipping cycle began in October and continued through June. The series covered the years 1988 through 1996.[3] Retail prices for bulk tomatoes, priced on a per pound basis, were obtained from a supermarket chain operating in a metropolitan area in the Southeast. This series covered the June 1988 through December 1993 period. The chain is the largest supermarket operator in the area and is a multiregional enterprise. Altogether, 150 weeks of shipping point data were matched by date with the retail data, encompassing over five growing seasons.

P_0 (the base period retail price) is calculated for the start of each harvest season by using the date of the initial price reported by the Florida Tomato Committee. Model results from the Houck procedure can be sensitive to initial starting values of the data (Powers, 1994); therefore, a four-week moving average of the retail price was used in place of $P_{i,0}$ at the start of each harvest cycle. This may be interpreted as the retailer having set prices relative to recent history as reflected in the past four-week period, instead of reformulating a new price at each time period just based on current and lagged shipping point prices. Given the stability of retail prices relative to shipping point (table 1), this appears to be a reasonable assumption.

Plots of the shipping point price and volume data indicate each year had its own pattern, primarily due to weather. The graphs supported the view that the analysis of price transmission should accommodate the volumes of shipments, which change from year to year. To incorporate variations in the volume of shipments, j represented millions of boxes shipped during a week (reported by the Florida Tomato Committee). This resulted in j taking on values from 1 to 4.

Transportation costs have been used in previous studies of vertical price transmission (e.g., Powers, 1994). However, they are not used here. The supermarket chain supplying the retail data purchases fresh produce from brokers and wholesalers

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[3] Tomatoes from this region comprised the primary supply for the United States during these months (Fahey, 1976; How, 1991). For this time period, the emergence of international competition in the winter fresh tomato market had already begun to occur (VanSickle, 1989).

in various locations, including those used in this study. Fresh produce transportation is part of the chain's distribution system, so transportation costs can be interpreted as fixed in the sense of no seasonal variation since warehouses, trucks, and drivers are part of the overhead (Eastwood, Carver, and Brooker, 1997). The routes (distances) between the shipping point and the retail outlets are fixed. Also, locally grown produce is not delivered directly to the chain's outlets.

Estimates based on the Prais-Winsten procedure (Judge et al., 1985) were used to identify the appropriate lag lengths for r and f.[4] In addition to identifying r and f, other model selection criteria included minimizing the mean square error and noting whether parameter signs were consistent with the Houck procedure.[5] After the appropriate GLS model was identified for each equation, the parameter estimates and error variances were used to initiate the Shiller procedure. A lag length of five was found to be best for both r and f.[6]

Empirical Results

Price correlations between the retail price series and lags of the shipping point prices are presented in table 1. A distinct pattern is revealed with respect to the retail series. The correlations consistently increase up to period t ! 2, and then begin to decline—consistent with the notion that lags in price response exist between the retail and shipping point levels. Furthermore, this pattern indicates a source of a priori information in that the lagged shipping point prices should follow a polynomial, specifically of the second degree, in order to increase the efficiency of the estimates. It should also be noted that differences in the correlation coefficients vary from period to period both up to and beyond their peak; thus, the Shiller procedure is more appropriate for incorporating such a priori information rather than restricting the lagged coefficients to lie exactly on a polynomial.

The Shiller estimates of equation (3) are reported in table 2. The rising and falling coefficients are of the correct sign and are significant across all time periods, indicating significant price adjustments occur each week of the transmission process. The R^2 indicates 55% of variation in period-to-period retail price changes and is explained by the lagged shipping point prices. The F-test for equation fit is significant at the .01 level.

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[4] Initial estimates of equation (3) involved finding the "best" OLS model and then using these results to begin the Shiller procedure. This was accomplished by arbitrarily setting $r, f = 8$, and eliminating the last lag periods if they were insignificant, then re-estimating equation (3). This process was continued until the last lag period was statistically different from zero at the 5% level. Results indicated significant first-order autocorrelation for a no-intercept regression equation (Farebrother, 1980). Consequently, GLS was utilized to identify the "best" model to begin the Shiller procedure.

[5] Estimated coefficients should be positive (negative) for rising (falling) shipping point prices.

[6] Notwithstanding the caveat noted by Conway et al. (1984), a Granger causality test was conducted using the data that initiated the Shiller procedure. The model entailed the five-week lag structure as well as five weeks into the future (Kennedy, 1998). The computed F-value for the unrestricted versus restricted regressions led to an inference of causality running from shipping point prices to retail prices.

Table 1. Descriptive Statistics and Lagged Price Correlations of the Shipping Point and Retail Price Series

(A)	**Descriptive Statistics**	
Item	Retail	Shipping Point
Mean ($)	1.22	9.48
Range ($)	0.39–2.99	2.99–38.67
Coeff. of Variation	0.34	0.62

(B)	**Lagged Price Correlations**						
	Shipping Point Price Periods:						
Item	t	$t-1$	$t-2$	$t-3$	$t-4$	$t-5$	$t-6$
Retail Series$_t$	0.67	0.73	0.77	0.69	0.59	0.46	0.36

Table 2. Shiller Estimates of the Shipping Point to Retail Price Linkage Relationship

Independent Variable	Coefficient (Std. Error)	Independent Variable	Coefficient (Std. Error)
SPR_t	0.00211* (0.00125)	SPF_t	0.00226* (0.00125)
SPR_{t-1}	0.00551** (0.00081)	SPF_{t-1}	0.00514** (0.00082)
SPR_{t-2}	0.00734** (0.00083)	SPF_{t-2}	0.00682** (0.00083)
SPR_{t-3}	0.00748** (0.00082)	SPF_{t-3}	0.00739** (0.00082)
SPR_{t-4}	0.00669** (0.00077)	SPF_{t-4}	0.00683** (0.00078)
SPR_{t-5}	0.00573** (0.00124)	SPF_{t-5}	0.00520** (0.00120)
R^2	0.55		
Equation F-value	11.905**		
Symmetry F-value[a]	0.04365		
Intra-period F-value[b]	0.00793		
Durbin-Watson statistic	1.289		

Note: Single and double asterisks (*) denote significance at the .10 and .01 levels, respectively.

[a] Distributed as $F(1, 119)$ under the null hypothesis.

[b] Distributed as $F(6, 119)$ under the null hypothesis.

Table 3. Seasonal Elasticities of Retail Price with Respect to Shipping Point Prices Evaluated at Beginning, End, Peaks, and Valleys of the Shipping Seasons

	Beginning		End		Peaks		Valleys	
Elasticity	$j = 1$	$j = 4$	$j = 1$	$j = 4$	$j = 1$	$j = 4$	$j = 1$	$j = 4$
ε_t	0.279	1.116	0.545	2.179	3.564	14.254	0.067	0.270
ε_{t-1}	0.591	2.365	1.654	6.617	6.745	26.980	0.177	0.707
ε_{t-2}	0.531	2.123	2.719	10.876	10.592	42.368	0.188	0.752
ε_{t-3}	0.351	1.406	3.666	14.665	7.436	29.744	0.191	0.766
ε_{t-4}	0.228	0.912	3.666	14.664	8.151	32.603	0.146	0.585
ε_{t-5}	0.122	0.486	3.078	12.313	6.983	27.931	0.102	0.407
ε^*_t	0.446	1.785	0.605	2.421	4.124	16.494	0.029	0.116
ε^*_{t-1}	0.760	3.039	1.586	6.342	7.023	28.092	0.043	0.172
ε^*_{t-2}	0.628	2.512	2.589	10.357	11.033	44.133	0.057	0.229
ε^*_{t-3}	0.335	1.341	3.639	14.556	7.759	31.036	0.024	0.097
ε^*_{t-4}	0.218	0.870	3.623	14.492	8.409	33.637	0.022	0.090
ε^*_{t-5}	0.115	0.459	2.693	10.770	5.760	23.041	0.017	0.068

Notes:

$$\varepsilon_{t-m} = \varepsilon_{SPR_{i,t-m},RP_{i,t}} = (\delta_{1,i,m} * j) * \left(\frac{SPR_{i,t-m}}{RP_{i,t}}\right) \quad \text{and} \quad \varepsilon^*_{t-m} = \varepsilon_{SPF_{i,t-m},RP_{i,t}} = (\delta_{2,i,m} * j) * \left(\frac{SPF_{i,t-m}}{RP_{i,t}}\right).$$

For the beginning (end) of the shipping season, $SPR_{i,t\,!m}$, $SPF_{i,t\,!m}$, and $RP_{i,t}$ were defined as their averages over the first (last) two weeks of each growing season for which observations were available on all independent variables. Their values corresponding to the peaks (valleys) of the shipping season were defined as averages taken over the significantly high (low) levels of shipments across the various seasons. The minimum and maximum shipment values are $j = 1, 4$, respectively.

The five-week lag for both rising and falling shipping point prices leads to the conclusion that the chain used the same amount of time to adjust retail prices to rising and falling shipping point prices. The F-value for symmetry leads to maintenance of the null hypothesis that the total impact of a positive shipping point price change is not significantly different from a negative shipping point price change. For the pairwise comparisons, the inference is that there is no difference in the chain's retail pricing behavior with respect to rising versus falling shipping point prices within the same lag period.

Table 3 shows seasonal elasticities of the retail price with respect to shipping point prices evaluated at the beginning, end, "peaks," and "valleys" of the shipping seasons using the minimum and maximum values of j (= 1, 4). For the beginning of the shipping season, $SPR_{i,t\,!m}$, $SPF_{i,t\,!m}$, and $R_{i,t}$ were defined as their averages over the first two weeks of each growing season for which observations were available on all independent variables. Similarly, averages over the last two weeks of each growing season were used to calculate the season-ending elasticities.

For the season-beginning elasticities, peak response at the retail level occurred in periods t ! 1 and t ! 2 for both the rising and falling prices. The peak responses of the season-ending elasticities occurred in periods t ! 3 and t ! 4 for both the rising and falling prices. Compared to the beginning of the shipping season, the chain seemed to wait longer to evaluate upstream price changes. Since shipments from the Florida market would soon end, the chain was likely beginning to assemble price information from other sources; therefore, the priority placed on reaction to the last few weeks of the Florida market was diminished and thus occurred later in the transmission process.[7]

Maximum and minimum shipments for the five harvest periods were averaged and used to generate a peak and a valley j. For elasticities evaluated at peak levels of shipments, the highest elasticity response for both the rising and falling prices clearly occurred in period t ! 2. This suggests that in periods of great supply, the chain will wait no longer than period t ! 2 of the transmission process to make its largest percentage retail price adjustment. Elasticities evaluated at valley levels of shipments indicate the highest retail-level response for the rising prices was period t ! 3. A different result was found for the falling prices, where period t ! 2 was clearly the peak retail response. The peak elasticities are much larger than those evaluated at valleys, suggesting that when shipments are very large, the chain is more sensitive to upstream price changes relative to periods of very low shipments. The limited shelf life of tomatoes likely caused the chain to be more sensitive to upstream price changes in times of great supply; therefore, moving the tomatoes quickly through the system became a top priority. The difference in timing is consistent with the Florida Tomato Committee data. Adjustments occur when prices fall rapidly, which would contribute to a slower estimated adjustment on the part of the chain to falling prices.[8]

A similar effect is found for each of the four seasonal elasticity pairs ($j = 1, 4$). The larger the value of j, the larger the elasticity. This leads to the inference that during periods of peak shipments, the chain becomes more responsive to shipping point price changes.

Conclusions

Empirical results suggest the retail chain is behaving efficiently in its reallocation of resources between what is available at the shipping point level and what is sold at the retail level. This finding is supported by the results that the long-run effects of upstream price increases on retail prices are similar to decreases and that the retailer responds similarly to intra-period rising and falling upstream price changes. Elasticities evaluated at various points in the Florida shipping cycle indicate market information from upstream sources readily influences retail-level price responsiveness. For example, changes in the chain's peak response to rising and falling shipping

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[7] A different argument could be made using the beginning of the shipping season as a point of reference. In order to capitalize on any potential trends that may be developing, the chain may choose to evaluate the Florida market more rapidly at the beginning of the season.

[8] This point was made by a reviewer.

point prices occur as it switches to and from reliance on the Florida market for its fresh tomatoes. Also, changes in supply at the shipping point level are reflected at the retail level, as noted by the differences in elasticities at the peaks and valleys of the shipping seasons.

The price symmetry found in this study is likely due to the biological nature of fresh tomatoes and how retailers in the distribution channel have adjusted to accommodate those demands. Tomatoes' limited shelf life helps motivate retailers to make timely changes in pricing strategies to attempt to ensure minimization of product loss. Also, to gain more control over the shelf life, most retailers can purchase fresh produce directly from shipping point sources—a practice which can facilitate efficient price adjustment by eliminating intermediate channel participants who may provide barriers to smooth transition of information through the distribution channel. This strategy dovetails with industry trends that were emerging during the time period with respect to the adoption of scanner technology as a management tool and the early stages of the efficient consumer response (ECR) emphasis.

Extensions of the current methodology of assessing market efficiency via price linkages were oriented toward providing an empirical model that is more reflective of the real-world environment in which market information is processed. The model has implications concerning the conjectured behavior of channel participants. Flexibility with respect to responding to the volume of shipments can lead to new insights for better identifying both the source of and reaction to economic stimuli within market distribution channels.

Such a model is well suited for the changing conditions facing the fresh produce retail sector today and is adaptable to other products and regions. The movement toward a global economy (e.g., GATT and NAFTA) and the changing domestic environment (e.g., proliferation of warehouse stores, food services, and restaurant industries) are forcing supermarkets to become more competitive in terms of their retail pricing behaviors and sources of products. Empirical methods for assessing a chain's competitive edge are therefore paramount and of potentially beneficial use for both public policy and private interests.

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