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SALES PROMOTION AND COOPERATIVE RETAIL PRICING STRATEGIES

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Abstract

Supermarket retailers make strategic pricing decisions in a high-frequency, repeated game environment both in buying and selling fresh produce. In this context, there is some question as to whether a non-cooperative equilibrium can emerge that produces margins above the competitive level. Supermarket pricing results from tacitly collusive equilibria supported by trigger price strategies played in upstream markets. Upstream activities are, in turn, driven by periodic retail price promotions. We test this hypothesis using a sample of fresh produce pricing data from 20 supermarket chains in markets distributed throughout the U.S. Our results support the existence of tacitly collusive non-cooperative equilibria in upstream and downstream markets.

Key words: dynamics, game theory, Nash equilibrium, perishables, supermarkets, tacit collusion, trigger prices.

1. Introduction

Grocery retailers use a variety of pricing strategies for both buying and selling perishable products. When selling to consumers, a particular supermarket may use an "everyday low price" strategy, or may choose to "meet the competition" (McLaughlin, *et al.*) or choose some point in between. When sourcing fresh produce, however, supermarket buyers may choose to sign contracts for relatively long periods of time, buy only in the spot market, or develop supply relationships with varying degrees of formality (USDA). However, price dynamics on both sides tend to exhibit certain regularities that contain significant implications for store profitability and economic efficiency. Although others consider strategic retail pricing (Lal and Matutes, Villas-Boas; Slade 1998), none consider the simultaneous determination of upstream and downstream prices. This paper provides an explanation of observed retail price patterns that explicitly considers the role of upstream oligopolistic interaction among retailers and tests this explanation using detailed, store-level retail scanner data.

At the retail level, prices for individual products in different stores within a market tend to move roughly in synch with one another (Lach and Tsiddon). For example, figure 1 shows chain-wide prices for Red Delicious apples for two chains in the same U.S. metropolitan market over the period 1998 - 1999. While the price movements are not lock-step, the series do exhibit co-movements that are clearly not perfectly random. For consumer packaged goods (CPG) this can at least be partially explained by the nature of vertical relationships between supermarket retailers and CPG manufacturers, many of whom have a considerable amount of latitude to set price through strong branding, product differentiation or consumer loyalty. For perishable products such as fresh produce, however, similar "list" prices do not exist. Although there are many different theoretical explanations for the observed pattern of retail supermarket prices

(Pesendorfer; Hosken and Reiffen; MacDonald), there are relatively few theoretical or empirical models that attempt to examine the role of upstream interactions among retail buyers.

Dowstream, or retail, prices among firms in the same market may appear to be set in a coordinated way for a number of reasons. First, any one of the many explanations for retail price fixity may be relevant. Whether due to menu costs (Levy et al.; Caplin and Spulber), internalization of consumer search costs (Lal and Matutes; Warner and Barsky; Bliss; Bils), counter-cyclical price elasticities (Rotemberg and Saloner; Abreu, Pearce, and Stacchetti), implicit contracts between retailers and their customers to maintain stable prices (Okun), constant marginal costs (Blinder, et al.), a failure among rival firms to coordinate prices (Ball and Romer), or their success in doing so (Stiglitz; Mischel), if retailers each maintain fixed prices, they will at least appear to be following similar strategies. None of these explanations, however, can easily explain synchronized price changes. As an alternative, Coughlan and Mantrala and Slade (1991) argue that under conditions of volatile demand, retail prices may appear to be set cooperatively if retailers use price reactions by rivals to provide information about their cost-structure. Given the number of products sold by most retailers, this assumption attributes an implausible degree of sophistication to store managers. A third explanation maintains that if dynamic price reactions are such that accommodative pricing strategies are optimal due to strategic complementarity, then prices can move together above the competitive level if products are sufficiently differentiated (Roberts and Samuelson 1988). There are two problems with this argument. First, retailers often sell identical products. Second, many retailers sell upwards of 25,000 products each, so coordination in downstream retail markets is difficult, if not impossible.

The multi-product nature of food retailing is well understood (Bliss). However, in *upstream* commodity markets retailers often interact with each other in bidding for supply one product at a time.[2] Therefore, it is possible that retail price coordination reflects the outcome of a repeated game played in wholesale, not retail, markets. In a repeated-game context, Green and Porter maintain that pricing above cost may reflect a non-cooperative equilibrium among firms that tacitly agree to follow a trigger-price strategy in which deviation is deterred by a credible threat of punishment (Porter 1983a; Green and Porter; Stiglitz). Their trigger-price model has received considerable empirical support in describing 19th century rail rates (Porter 1983b; Lee and Porter; Ellison) and airline fares (Brander and Zhang) in downstream markets, and beef packing (Koontz, Hudson, and Garcia) and processing potatoes (Richards, Patterson, and Acharya) in upstream food markets. Consequently, this model may also explain both wholesale and retail pricing behavior by grocery firms.

Green and Porter's argument is that firms in concentrated industries may be able to enforce tacitly collusive price setting arrangements through punishment strategies based on the shared recognition of a trigger prices. When firms have complete, yet imperfect information regarding rival behavior, they begin in a state of collusion, but revert to Nash behavior if the trigger price is violated until a cooperative equilibrium is restored (Friedman). With complete and perfect information, and with sufficient patience, such a strategy can support a collusive outcome in a repeated game.[3] When information is less than perfect, however, a firm does not know whether a low price (in the case of output market rivalry) represents a defection by a rival, or simply results from adverse market conditions. Industry equilibria maintained by trigger

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[2] This is particularly true in fresh produce retailing (the empirical example in this paper) because few suppliers sell more than two or three different items.

[3] This is by no means the only effective punishment strategy. Abreu, Pearce and Stacchetti show that, in a more general model than Green and Porter, optimal punishments are less benign than a reversion to Nash strategies and can last for only a single period.

strategies produce discontinuous patterns of behavior, varying between Cournot and somewhat less than perfect collusion.[4] As Ellison explains, however, firms will not cheat in equilibrium, so neither will they punish – reversion to Nash during intermittent price wars is sufficient to ensure that the triggers are effective. More important for current purposes, the resulting price process is consistent with a number of observed retail pricing puzzles.

Indeed, the trigger-price model provides an explanation for one pervasive feature of fresh produce retailing that no one has been explain to explain in a definitive way – price promotions, or "sales." Typically, temporary price promotions are thought of as a means of price discriminating among consumers of differing types or shopping intensity (Pesendorfer; Varian; Salop and Stiglitz). Villas-Boas provides an empirical test of one such "competitive" model of price promotions and suggests that "...price competition....in fact, does not occur, and price promotions are completely predictable..." (p. 86). However, these explanations ignore the importance of upstream interactions. When planning a temporary price promotion, a retailer must obtain commitments from suppliers to deliver a greater volume of produce than usual. This usually requires the retailer to pay premium prices. Rivals, lacking adequate wholesale price information, interpret their drop in market share as either a random fluctuation in demand or, if large enough, a violation of its "trigger share." A price war in the input market ensues. In equilibrium, this one-shot reversion to Nash behavior is sufficient to ensure the validity of the trigger itself. Therefore, price promotions effectively serve as facilitating mechanisms for tacit input-market collusion among retailers – allowing firms to share and filter information without

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[4] Green and Porter develop their model assuming Cournot rivalry, while Porter (1985) considers the same example from a Bertrand perspective. As Porter (1985) notes, the models differ very little.

explicitly coordinating their behaviors.[5] Although the necessary conditions for this type of interaction exist in the retail supermarket industry, there are as yet no tests of the trigger-price model in this context.

Consequently, the objective of this paper is to determine whether a well-understood model of non-cooperative pricing behavior explains observed patterns of retail and wholesale produce prices in U.S. retail and wholesale markets. In achieving this objective, we first describe how the trigger-price model applies to fresh produce pricing in the retail grocery industry. Next, we derive an empirical model that is able to test the critical hypotheses that follow from the trigger-price model. In the third section, we describe both the retail-scanner data and the wholesale produce-price data necessary to properly identify retail and input-market pricing behaviors. The fourth section consists of a presentation and discussion of the empirical results regarding the central hypotheses of the paper. A final section offers some conclusions regarding the findings with respect to retailer conduct in both input and output markets.

2. Conceptual Model of Trigger-Price Strategies

There are, in general, three groups of theories that seek to explain dynamic price processes that arise from games of repeated strategic interaction among oligopolists (Slade 1990): (1) learning models where firms use price wars to cause rivals to reveal their costs (Slade 1987), (2) cyclical models wherein the strength of expected industry demand influences the incentives to collude or defect (Rotemberg and Saloner), or (3) imperfect monitoring models (Green and Porter; Abreu,

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[5] Implicitly, the trigger price strategy is a two-stage game that is solve by backward induction. In the second-stage, retailers compete in downstream prices and establish an expected amount of consumer demand. To serve this demand, retailers compete in upstream markets for available supply. Because, in real time, the wholesale transaction must precede the retail, it is the first stage of the game.

et al.). Because the grocery industry is relatively stable, supermarket chains are relatively few in number, and individual buyer-representatives compete to acquire fresh produce daily on a year-round basis with poor market price information, the "trigger price" model seems to be the most plausible explanation for produce price dynamics.

In fact, the way in which fresh produce is bought and sold is highly conducive to the type of information flow required for an imperfect monitoring model to function. Although retail prices tend to be well publicized through regular food-page ads in local newspapers or inserts, wholesale price information is less reliable. In fact, USDA no longer reports same-day quotes of shipping point prices, so industry members have little confidence in the price data that is available. This is an important point because retailers typically purchase fresh produce several weeks prior to a retail promotion in order to ensure that sufficient supplies are available. If price data are unreliable, rival retail buyers are unlikely to notice any rise in wholesale prices that may signal a rival's impending promotion. On the other hand, most commodity trade associations report volume movements on a weekly basis, so buyers can quite accurately estimate their share of the market. Therefore, retailers must filter imperfect information regarding rival strategies through changes in their market share. Although researchers often describe retailers as competing in output prices, at least in the case of fresh produce the game is played in the input market rather than the output market as wholesale price changes both lead and facilitate retail price strategies.[6] Consequently, periods of relatively low retail prices and high wholesale prices are expected to coincide with periods of comparatively competitive behavior, while cooperative, non-promotion periods imply high retail margins. We develop this explanation more formally in

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[6] This observation is consistent with findings from a preliminary analysis of the data (available upon request). Salop and Stiglitz provide the theoretical justification for why wholesale prices should be expected to lead retail prices.

a trigger-price model similar to Green and Porter, but with both input and output uncertainty.

Assume the produce-retailing industry consists of $i = 1, 2, \ldots N$ firms, each selling $j = 1, 2, \ldots M$ products. Retailers buy produce in the wholesale market, and then resell the same products to consumers. Further, assume that retailers convert produce at the wholesale level to saleable goods using the same, fixed proportions technology so that raw inputs are separable from other, non-farm inputs. Therefore, the production technology can be written as: $q_{ij} = \lambda_{ij} x_{ij}$ where x_{ij} is the amount of produce of type j purchased by retailer i, q_{ij} is the amount of j sold by the ith retailer, and λ_{ij} is the proportionality constant, here assumed to be 1. Retailers compete for available supply in wholesale markets by paying an input price, w_{ij}, for an amount of raw inputs described by an upstream supply curve: $x_{ij}(w_{ij}, \mathbf{w}_{-ij}\, \mathbf{z}_1)$, where $\mathbf{z}_1$ is a vector of supply-shifting variables and $\mathbf{w}_{-ij}$ is a vector of rival firm ($-i = 1, 2, \ldots, n - 1$) input price bids. Downstream, retail demand depends on the firm's own retail price, all rival prices and a vector of demand shifters, $\mathbf{z}_2$, so that $q_{ij}(p_{ij}, \mathbf{p}_{-ij}, \mathbf{z}_2)$. Total industry sales are: $Q_j = \sum_i q_{ij}$ for each product j, but realized sales for each firm are a fraction of the total market. Each firm's share is subject to a random multiplicative disturbance so that: $b_{it} = \psi_{ijt}(q_{ijt}/Q_{jt})$, where ψ_{ij} are i.i.d with continuous density f and distribution function F. Market share, however, only imperfectly reflects the input-price choices of other firms in the industry.[7] Assume firm i maximizes the present value of its expected future profits by following a contingent strategy in input prices, which is defined as an infinite sequence of bids where the bid at time t depends recursively on the history of past realizations of market share, b_i, such that: $w_{it} = s_{it}(b_0, b_1, \ldots, b_{t-1})$ for each product, j. Based on

[7] Green and Porter suggest this alternative to their own model, wherein firms monitor the market price as an imperfect signal of others' shipment levels, as more consistent with a price-setting industry structure.

own and rival strategies defined in a similar way, the objective function becomes:

$$V_i(\boldsymbol{s_i}) = \max_{\boldsymbol{s_i}} E[\sum_{t=0}^{\infty} \beta^t \pi_i(\boldsymbol{s_i}, \boldsymbol{s_{-i}})], \tag{1}$$

for a set of rival strategies $\boldsymbol{s}_{-i,}$ a discount factor β^t, and input prices w_t. Under perfect information, rivals' actions are known with certainty and a collusive equilibrium can be supported if a punishment strategy is individually rational for all firms.[8] Individual rationality requires that the value of the firm under a collusive strategy be greater than the value of a single-period defection, followed by reversion to Bertrand prices: $V_i(w_i) > \pi_i(w^*) + \beta^t V_i(z_i)$ where w_i is the price a firm pays in "normal" or collusive periods, and z_i is the price in reversionary or Bertrand periods. Because information is assumed to be imperfect, however, the firm chooses between w_i and z_i based upon the only signal that can be observed – its realized market share. Consequently, a discontinuous pricing strategy results depending upon the relationship between market share observed in the previous period and a trigger share: $\bar{b}$:

$$w_{i,t} = \begin{bmatrix} w_{i,t}, & b_{i,t-1} > \bar{b}_i \\ z_{i,t}, & b_{i,t-1} < \bar{b}_i \end{bmatrix}. \tag{2}$$

Stanford shows that such discontinuous strategies are necessary to support sub-game perfect collusive equilibria except in the trivial case where continuous reactions specify replication of the

[8] This is the Folk Theorem of Fudenberg and Maskin, the primary implication of which is that there is potentially many equilibria in a repeated game with discounting.

Nash component game outcome.[9] Within the broad class of discontinuous strategies, Porter (1985) argues that there are many possible equilibrium price and punishment-period length pairs, so it remains to describe the optimal strategy.

Defining the single-period profit during cooperative periods as $\pi_i(w_i)$ and that in reversionary periods as $\pi_i(z_i)$, the value of the firm initially in a cooperative period is given by the weighted average of the present value of profits from operating in each period:

$$V_i(w_i) = \pi_i(w_i) + \beta Pr(\bar{b}_i < \psi_i(q_i/Q))V_i(w_i) + Pr(\bar{b}_i \geq \psi_i(q_i/Q))[\sum_{t=1}^{T-1}\beta^t \pi_i(z_i) + \beta^T V_i(w_i)], \qquad \textbf{(3)}$$

for reversionary periods of length T. Recognizing that $Pr(\psi_i(q_i/Q) < \bar{b}_i) = F(\bar{b}_i/(q_i/Q))$, (3) can be rewritten as:

$$V_i(w_i) = \frac{\pi_i(w_i) - \pi_i(z_i)}{1 - \beta + (\beta - \beta^T)F} + \frac{\pi_i(z_i)}{1-\beta}, \qquad \textbf{(4)}$$

which simply states that the expected present value of firm i is equal to the present value of setting prices at the Bertrand level forever, plus the discounted value of profit earned during collusive periods.

Maximizing the value of the firm, therefore, gives the following first order condition:

$$V_i(w_i) = \pi_i^{\prime}(w_i)[1 - \beta + (\beta - \beta^T)F] + (\pi_i(w_i) - \pi_i(z_i))[(\beta - \beta^T)f(\partial F/\partial s^i)] = 0, \qquad \textbf{(5)}$$

[9] Nevertheless, Slade (1987, 1990) develops a model wherein price wars are an equilibrium outcome of continuous dynamic reaction function strategies.

which states that the incremental benefit from cheating on an existing collusive arrangement ($\pi_i(w_i)$) must equal the expected marginal loss that is incurred if rivals interpret the fall in market share correctly and adopt a punishment strategy (Green and Porter). Because this condition defines a subgame perfect strategy, every firm in the industry will indeed be expected to follow it and, therefore, never completely defect from the cooperate / punish cartel. To test whether or not the data are consistent with the trigger price model, we develop an empirical approach that can identify the exercise of market power during collusive regimes, and the endogenous switch to more competitive pricing.

3. Empirical Test of Cooperation in Semi-Perishable Produce

Because the price pattern shown in figure 1 could be due to changes in wholesale prices, retailing costs or demand that are common to all stores in a particular market, it is necessary to control for these other factors in testing for the exercise of market power. Consequently, we use a structural model of industry supply and demand in which firm conjectures of rival behavior are used to test whether retailers exercise market power in either input markets, output markets, or both (Bresnahan). Specifically, the structural model consists of equations that represent: (1) produce supply, (2) retail demand, and (3) retailer margin determination. Consistent with the conceptual model of retailer pricing, the empirical model also allows for the fact that rivals interact in a discontinuous way, alternately reverting to Nash behavior or cooperating according to their assessment of rival actions. Allowing for multiple pricing regimes represents the primary empirical challenge to testing for trigger-price behavior. Indeed, estimating a model that consists of discontinuous regimes of firm market power requires the identification of two sets of latent, or unidentifiable, conduct parameters where the switching behavior between the two is determined endogenously. To do so, we use a finite mixture estimation (FME) approach applied to a structural model of firm conduct that consists of multiple behavioral regimes.

Assume the cost of selling product *j* by firm *i* depends on the volume sold and a vector of non-farm input prices, $\boldsymbol{v}$: $c_{ij}(q_{ij}, \boldsymbol{v})$. Total cost is separable between buying and selling activities for each product so the profit maximization problem facing retailer *i* is:

$$\max_{w_i, p_i} [\pi_i] = \max_{w_i, p_i} [p_i q_i(p_i, \boldsymbol{p}_{-i}) - w_i x_i(w_i, \boldsymbol{w}_{-i}) - c_i(q_i)] \quad \forall\, j. \qquad \textbf{(6)}$$

where $\boldsymbol{p}_{-i}$ and $\boldsymbol{w}_{-i}$ are vectors of all (n - 1) rival firm's output and input prices, respectively and the demand and supply functions are as described above. Allowing for data limitations, assume retailers and their rivals face a common wholesale price $(\tilde{w})$, and a common retail price $(\tilde{p})$ so that $\epsilon_i = \partial q_i / \partial \tilde{p}$ is the slope of the demand curve facing retailer *i* and $\eta_i = \partial x_i / \partial \tilde{w}$ is the slope of the input supply curve.[10] Further, assume the retail-price conduct parameter is $\phi_i = \partial \tilde{p} / \partial p_i$ while in input prices, the conduct parameter is: $\theta_i = \partial \tilde{w} / \partial w_i$. Taking the first-order conditions to (6) and substituting each of these parameters provides an expression for the retail-wholesale margin:

$$m_i = (p_i - w_i) = x_i(\eta_i \theta_i)^{-1} - q_i(\epsilon_i \phi_i)^{-1} + c_{q_i}, \qquad \textbf{(7)}$$

for each product, suppressing the *j* subscript, where η_i is the slope of the supply curve facing each firm, θ_i parameterizes firm *i*'s conduct in the wholesale market, ϕ_i is an estimate of firm i's conduct in the retail market ($\theta_i = \phi_i = 0$ implies Bertrand - Nash behavior in the wholesale and

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[10] The wholesale price data consists of a single, weekly Red Delicious apple price series published by the *Washington Growers' Clearing House.* While we have retailer-specific selling prices, rivals differ in both number and description for each market, so the definition of a "rival price" is problematic. McLaughlin, *et al.* suggest that retailers set prices based on their perception of "the market," but change prices only slowly due to adjustment costs, so this assumption is justified on the basis of industry practice

retail markets, respectively, during reversionary periods and θ_i, $\phi_i > 0$ during cooperative periods), and ϵ_i is the slope of each firm's perceived retail demand function.[11] Expressed in terms of the trigger model, the estimated conduct parameters indicate the extent to which retailers are able to set retail prices that are higher, or wholesale prices that are lower, than the Bertrand - Nash level during cooperative periods.

In order to identify these parameters, we estimate supply as a function of the wholesale price paid by firm *i*, an interaction term between firm *i*'s wholesale price and a key production input price (z_{11}), and prices of alternative products that substitute in supply (z_{1k}) (Bresnahan):

$$x_i(\tilde{w}, z_1) = \alpha_0 + \alpha_i(\tilde{w}/z_{11}) + \sum_k \alpha_k z_{1k} + \mu_2, \qquad \textbf{(8)}$$

where $\eta = \alpha_i$ is the slope of the supply function. Retail demand is also specified in direct form where retail quantity is a function of a retailer's own-price, an interaction term between firm *i*'s retail price and a measure of personal disposable income (z_{21}), and demand-shifters such as prices of substitute goods and seasonal dummy variables (z_{2k}):

$$q_i(\tilde{p}, z_2) = \gamma_0 + \gamma_i(\tilde{p}/z_{21}) + \sum_k \gamma_k z_{2k} + \mu_3, \qquad \textbf{(9)}$$

where $\epsilon = \gamma_i$ is the slope of the retail demand curve. To account for seasonality, the estimated model includes a set of monthly dummy variables. Moreover, both supply and demand models are estimated using two-stage least squares due to the likely endogeneity of wholesale and retail prices, respectively.

Retailing costs in (7) are assumed to be Generalized Leontief. Specifically, for a single

[11] Although the conjectural variations solution has been widely criticized in the industrial organization literature, Cabral shows that it is an exact reduced form of a dynamic, quantity-setting repeated game.

output (q_i) and m input prices (v_k), the GL cost function becomes:

$$c_i(q_i, \mathbf{v}) = q_i \sum_k \sum_l \gamma_{kl}(v_k v_l)^{1/2} + q_i^2 \sum_k \gamma_k v_k + \mu_{1i}, \qquad \textbf{(10)}$$

where μ_1 is a random error term, and the set of input prices include indices of fuel and electricity prices, business services, and a measure of wages for workers in food retailing. Equations (8) - (10) are then substituted into (7) to arrive at an estimable form for each retailer's margin equation.

The conceptual model also suggests that retailer conduct varies over time, albeit in a discontinuous way. In fact, if sales promotions are to serve as facilitating mechanisms for the trigger-price equilibrium described above, then the degree of market power is expected to fall with sales volume.[12] To test this hypothesis, we write each conduct parameter as a linear function of quantity:

$$\begin{aligned} \theta(q_i|\delta) &= \delta_o + \delta_1(q_i) + \mu_4, \\ \phi(q_i|\tau) &= \tau_o + \tau_1(q_i) + \mu_5. \end{aligned} \qquad \textbf{(11)}$$

for firm i. Although it is common practice to estimate equations (8) - (11) simultaneously, in this study we estimate product supply, retail demand and the fresh produce margin equations sequentially due to the added complexity of the multiple-regime finite mixture model.

Essentially, a finite mixture approach maintains that observations of the dependent variable, retail margins in the current case, are not drawn from one distribution, but rather two

[12] A facilitating mechanism is any institutional or behavioral regularity that may allow the players to send and receive signals as to changes in market share or volume objectives. In the JEC example of Porter (1983b, 1985), published shipping amounts serve this purpose, while in Richards, Patterson and Acharya contract negotiations play a similar role.

distinct distributions described by unique sets of parameters. In general, Titterington, Smith, and Makov define $f(m_i)$ as a finite mixture distribution of margins over k distinct regimes if:

$$f_i(m_i) = \rho_1 f_{1i}(m_i) + ... + \rho_k f_{ki}(m_i) \quad \textbf{(12)}$$

where the mixing weights are defined as $\rho_j > 0, \sum_j \rho_j = 1, \; j = 1,2,...,k$ and the individual densities must, of course, meet the restrictions that: $f_j > 0, \; \int f_j(m_i) dm = 1$. Thus, the density for margins is a probabilistically weighted average of each of the component densities (f_j), each with its own mixing weight. Assuming product margins are normally distributed, and simplifying the mixture distribution to represent only two regimes, the density becomes:

$$f_i(m_i|\Omega) = \rho\psi(m_i|\mu_1,\sigma) + (1 - \rho)\psi(m_i|\mu_2,\sigma), \quad \textbf{(13)}$$

where ψ is the normal density function, and $\mu_r = \boldsymbol{Z}\boldsymbol{\alpha_r}$ for regime r and a vector of explanatory variables, $\boldsymbol{Z}$. We use Wolfe's modified likelihood ratio test to test the null hypothesis that the parameter vectors in each regime are equal. Wolfe's test is an approximation to a likelihood ratio test that is chi-square distributed with test statistic: $S = (2/N)(n - 1 - d - (C_1/2))\log L$, where L is the value of the likelihood ratio under the null hypothesis of no mixture, N is the sample size, C_1 is the number of components in the mixture (two in this case), and d is the dimension of the underlying normal distribution with $2d$ (C_1 - 1) degrees of freedom. We determine whether two regimes are similar with a joint test of the similarity of their entire parameter vectors, but particular interest lies in potential differences between firms conduct parameters, or the amount of market power they possess. Modifying equation (7) to be consistent with the switching-regression logic, the estimated margin model becomes:

$$m_{it} = \begin{bmatrix} c_{it} & & & \text{with prob. } \rho \\ c_{it} & +x_{it}(\eta_{it}\theta_i)^{-1} & - \; q_{it}(\epsilon_{it}\phi_i)^{-1} & \text{with prob. } (1-\rho) \end{bmatrix}, \qquad \textbf{(15)}$$

for each product *j*.

Because the separation points between the two regimes are unobservable, unlike the JEC data used by Porter (1983b, 1985), we use the expectation / maximization algorithm (EM) described by Dempster, Laird, and Rubin. Upon convergence, the resulting parameter estimates possess the asymptotic properties of maximum likelihood estimates.

4. Data Description

The trigger-price model is estimated using a sample of firm-level wholesale and retail price and shipment data for US fresh apples. Apples provide an excellent opportunity to test the trigger-price model because: (1) uniquely reliable wholesale price data are available on a weekly basis, by variety for apples sold from Washington state, (2) the perishability of fresh fruit places buyers in a favorable bargaining position relative to sellers in the upstream market, (3) fresh produce suppliers tend to be small relative to one another, so can be assumed to be price-takers, and (4) consumers often choose a supermarket based on the quality and value of its fresh produce, so "flagship" produce items often represent points of competition among retailers (Supermarket News). Further, to account for heterogeneity in regional produce markets, we estimate independent pricing models for each chain and market in the sample. Specifically, the sample includes retail supermarket chains in city-markets located in the Northeast, Southeast, Midwest, Southwest, West Coast, and Atlantic Coast. The cities and names of the chains are withheld for reasons of confidentiality. For each chain, we have 104 weekly observations over the period January 1998 to December 1999 consisting of price per pound and number of pounds sold from all stores of a given chain. Washington Red Delicious apples are chosen as representative of the price dynamics of the entire category in order to control for aggregation errors over products of different quality, local supply, or local preferences.[13] [14]

The source of all retail data is the Information Resources Incorporated (IRI) retail perishables scanner data base. These data, commonly used for category management purposes by product commissions and large shippers, includes measures of: (1) weekly movements (quantity, in lbs.) of a given UPC or PLU coded product by chain, and retail market; (2) listed selling price of the product by chain, and market; and (3) number of stores within the chain selling the product. Price differences between bagged and bulk apples are corrected using the hedonic price-correction method suggested by Goldman and Grossman, which provides a bulk-equivalent apple price for each market-chain-week observation. Although the retail price for individual apple varieties and sizes typically change very little over the sample period, it is necessary to aggregate this way in order to match the shipping-point price data, which does not differentiate among apples of the same variety beyond controlled versus regular storage. Regional, personal disposable income per capita data are from the Bureau of Labor statistics and are used to "rotate" the demand curve and identify the conduct parameter in each market. Retailing cost data,

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[13] While the margin equation includes only the representative product price, we control for multi-product retail pricing effects through the demand equation (Bliss, Giulietti and Waterson). Moreover, the focus on price determination for a single product is consistent with recent retail pricing research by Pesendorfer, who finds that demand for a single SKU (stock-keeping unit) is independent of other product prices.

[14] Due to space limitations, the results reported here concern only Washington Red Delicious apples, although we estimate the model for California green seedless grapes, California fresh Navel and Valencia oranges, and Florida grapefruit as well. Results for other commodities are broadly similar and are available from the authors on request.

however, are common to all stores in a given market.

Labor constitutes the major component of retailers' costs. Wage data for workers in the retail grocery industry are from the Bureau of Labor Statistics *National Employment, Hours, and Earnings* report on a monthly basis for 1998 and 1999. This report also provides average weekly earnings for workers in the advertising, business services, and the FIRE (finance, insurance, and real estate) sector, each of which provides a measure of input prices at the retail level. All monthly data are converted to weekly observations using a cubic spline procedure. Marketing costs also include transport costs from the growing region to the destination market. For this purposes, the USDA-AMS *Truck Rate Report* provides estimates of weekly trucking costs between Washington state and each destination market.

Wholesale prices are defined as the shipping-point price paid at the source on a free-on-board (FOB) basis. For Washington apples, the price represents a weekly average over all sizes and grades of Red Delicious apple as reported by the Washington Growers' Clearing House. Because the proportion of regular-storage and cold-storage apples that are shipped varies each week, the price is simply a weighted average of each type. To estimate the extent of any rotation in the supply curve (ie. non-parallel shifts required to identify the conduct parameter), we divide the FOB price by the wage rate paid to apple-workers during the relevant week. Wage data are obtained from the Washington State Employment Security Department's *Labor Market Information* report. Washington Growers' Clearing House reports also provide monthly shipments for all apple varieties to all domestic destinations. Finally, all prices are converted to a dollars per pound measure in order to compare directly to the retail price data.

4. Results and Discussion

In this section, we present the results from estimating (16) for each retail chain and market, as well as the associated wholesale supply and retail demand estimates for fresh apples. Because the data does not include retailer-specific wholesale prices, we simplify equation (9) by defining a single wholesale apple market and impose the assumption defined above that all cross-prices responses are proportional to the own-price response. Table 1 provides two-stage least squares estimates of this market supply function for Washington Red Delicious apples. Although shippers have the ability to determine when to bring their apples out of storage, we account for any potential seasonality in supply by including a set of qualitative monthly variables. Based on the results in table 1, the model provides a relatively good fit to the data ($R^2 = 0.746$), there is no autocorrelation (d = 2.287), nor heteroskedasticity (BP = 8.971) so the remaining results use the unadjusted two-stage least squares parameters.[15] Because price variable in this specification is a ratio of the wholesale price to the harvesting wage, the elasticity of supply varies over the sample period, averaging 1.841. Further, each exogenous variable has the expected effect on supply and is statistically significant.

[Table 1 in here]

Unlike supply, retail demand is market-specific. Therefore, table 2 shows demand curve estimates for each market, using two-stage least squares to account for the endogeneity of sales and a fixed-chain effect panel data estimator to account for unobserved chain-level heterogeneity. Again, we impose the assumption that cross-price responses are inversely proportional to the number of retailers in the market and directly proportional to the own-price response (in absolute value), so retailer conduct may be summarized by one conduct parameter in equation (8).

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[15] We use a standard Durbin-Watson (*d*) test for autocorrelation, and a Breusch-Pagan test for heteroskedasticity.

Clearly, both the own- and cross-price elasticities of retail demand vary widely among markets. Moreover, the majority of chain-specific constants are significantly different from zero and suggest retail price differences ranging from $0.005 per pound in market one, to over $0.13 per pound in market six while only two markets exhibit inelastic demand for apples, with the majority in the range of -1.800 to - 2.400. Given these differences in demand among markets, we expect the retail-market conduct parameters to vary significantly as well

[Table 2 in here]

Using the estimated supply and demand curve slopes from tables 1 and 2, we then estimate the pricing equation (16) as a mixture of normals. Although the model in (16) is potentially consistent with other explanations of retailer pricing behavior, rejecting the null hypothesis of a single regime provides strong evidence in support of the maintained hypothesis. The trigger-price hypothesis is tested in two ways: (1) a Wald test of the mixture parameter, and (2) Wolfe's modified likelihood ratio test for single versus multiple-regimes with the results of both shown in table 3. If the Wald test statistic is significantly different from zero, then we conclude that the data are more consistent with two regimes that one. Clearly, this is indeed the case in each of the sample markets. Recognizing that the likelihood function in a mixture model is not well-defined at the boundaries of each component distribution, Wolfe derives a modified likelihood ratio test that also serves as a test of the mixture specification. As with the mixture parameter, we reject the null hypothesis of a single regime, providing further support for the trigger-price model.

[Table 3 in here]

An additional, albeit indirect, test of the central hypothesis of the paper – that price promotions serve as facilitating mechanisms for tacit collusion – consists of examining the impact of sales volume on conduct in both upstream and downstream markets. As the results in Table 3 show, both conduct parameters tend to fall in unit sales. We interpret this as evidence that retailers are less likely to cooperate and more likely to revert to Nash behavior during promotional periods because of their pre-commitment to larger volumes. As the mechanism through which retailers ensure the viability of the market share triggers, price promotion thus facilitates tacitly cooperative pricing arrangements. Such evidence is also consistent with the theoretical model of promotion model developed by Lal wherein sales are part of a pure strategy equilibrium in an infinitely repeated game between two cooperating retailers implicitly acting in concert to deny entry to a third.

Modeling quantity-varying conduct in this way plays an additional role. By allowing each conduct parameter to vary with weekly shipments, we disaggregate the test for cooperative pricing into two components: (1) a purely strategic element that captures how firms react to decisions taken by their rivals, and (2) the impact that shipment levels have on their ability to maintain a tacitly cooperative outcome in a non-cooperative game context. In their buying activities, we find the second effect to be negative in thirteen of the twenty chain-market pairs and significantly so in nine of these. In the output market, a similar result obtains. Specifically, fourteen of the twenty parameter estimates are negative, and ten of these are significantly so at a 5% level, while only two are significantly greater than zero. The fact that not all of these estimates are significant is hardly surprising given what we know about the diversity of retail pricing strategies. Perhaps more importantly, retailers that appear to exercise significant market power upstream do so downstream as well. This result provides support for the linkage between buying and selling activities that the theoretical model predicts.

Trigger-price theory also suggests that reversion to Nash ought to be rare. Indeed, Porter

(1985) finds that the "...percentage of time spent in reversions to relatively competitive behavior increased from 26.6% to 40.1%..." in response to an increase in the number of firms in the JEC from four to five (p. 426). The results reported in table 3 are broadly similar to Porter (1985) when compared across different regional markets. In fact, the three lowest cooperation rates occur in the two markets with the largest numbers of competitors – the Southwest and West. Although this is only indirect evidence in favor of the trigger-price model, it does show that the results are consistent with previous findings in other industries. Although these mixture weights imply punishment frequencies somewhat higher than Porter (1985), the supermarket industry, particularly in perishable products, is far more dynamic and contact among industry members more prevalent than in industrial markets. Equally important as the size of this parameter, however, is its statistical significance. Because each mixture probability is statistically different from zero, the results in this table lend strong support to the existence of separate pricing regimes of cooperation and punishment.

Behavior within each regime, however, is not uniform across markets. In the Northeastern sample market we find that tacitly cooperative behavior among retailers, in both input and output markets, explains a significant proportion of their gross margin. Given that competitive upstream (downstream) pricing implies a conduct parameter value of: $1 + \theta_i = 0$ ($1 + \phi_i = 0$), retailers appear to exercise a considerable degree of market power both upstream and downstream. However, the extent of market power varies not only among retailers and geographies, but also between upstream and downstream markets. Whereas retailers in 14 of 20 chains have significant conduct parameter values on the buying side, nearly all, or 18 of 20, are statistically significant when selling to consumers. In terms of retailer buying activity, the conduct parameter varies from 0.016 for one chain in the Southwest to a high of 1.562 for a chain in the West. Although this latter result is somewhat of an anomaly, it is nonetheless generally apparent that retailers do indeed appear to exercise a considerable amount of market power in sourcing produce. Moreover, excluding the outlying observation in the West, the results suggest that deviation from competitive input prices is consistent throughout the industry. On the selling side, the conduct parameter estimate varies from a low of 0.006 for a chain in the Midwest to a high of 1.524 in the Atlantic Coast region. In general, the estimated conduct parameters at the retail level tend to have a greater dispersion than the wholesale-conduct estimates. This result supports the collusive mechanism described in this paper, because the input-market trigger price hypothesis suggests that cooperation throughout the vertical channel across retailers is driven by buying strategies. If output markets were instead the focus, then we would expect to see much more consistent behavior on the selling side of the market. Moreover, the results in table 3 suggest that, in general, retailers are able to exercise a much lower level of market power in the retail market relative to the wholesale side. Combining both sets of results, however, the estimates suggest that retailers tend to follow cooperative pricing strategies in both upstream and downstream markets. In terms of the theoretical predictions of the trigger-price model, this result is not surprising as cooperative behavior in input markets is facilitated by output market activities.

5. Conclusions and Implications

This study presents an empirical test of supermarket retailer pricing behavior in wholesale and retail markets for fresh produce. The central hypothesis is that retailers are able to sustain tacitly cooperative pricing arrangements, both in buying and selling activities, through a trigger-price strategy in which sales promotions facilitate coordination through upstream markets.

We test the implications of this model using a case-study of Washington Red Delicious apples – a product for which we have a uniquely rich data set, both on the selling and buying sides. The data consists of two years (1998 and 1999) of highly disaggregate, store-level, weekly retail-scanner price and sales data from six major metropolitan markets in various regions throughout the country. On the buying side, the supplier price data consists of shipping-point prices and volumes obtained from the Washington Growers' Clearing House. To determine whether a trigger strategy is able to explain the wholesale and retail apple price dynamics exhibited in this data, we estimate a model that allows for separate regimes of cooperation and reversion and test against a single-regime, competitive model. In a majority of markets, we reject the null hypothesis of a single pricing regime so conclude that retailers do indeed follow discontinuous pricing patterns. However, this result is consistent with a number of alternative behaviors, so we also test whether retailers' conduct supports a cooperative equilibrium. This more specific test also fails to reject the trigger price hypothesis. Finally, we also reject the null hypothesis that retailer pricing conduct is independent of their sales promotion activities, thus providing support for the hypothesis that retailers use periodic promotions as facilitating mechanisms for tacitly cooperative pricing strategies.

These results have many implications for retail pricing strategy. First, and most obviously, promotion can have benefits that go beyond the usual price-discrimination or purchase-acceleration rationales (Varian) to include strategic benefits among rival sellers. Second, behavior that may appear to be explicitly collusive can, in fact, be the result of unintentional, or tacit behavior to maximize profit when rival reactions to one's own actions are taken fully into account. Third, when evaluating profit maximizing decisions by retailers, researchers must include the fact that they interact both upstream and downstream in each of their product markets.

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Table 1. Apple Supply Function 2SLS Estimates

Variable[a]	Coefficient	t-ratio
w_1 / v_1	7.438	4.810
v_2	-0.094*	-3.022
v_3	-1.046*	-7.352
v_4	-7.402*	-6.011
z_{11}	-69.977*	-6.657
z_{12}	-4.338*	-17.347
t	0.184*	16.883
Jan	-10.269*	-16.098
Feb	-7.877*	-9.799
Mar	-7.229*	-9.594
Apr	-7.111*	-9.672
May	-6.706*	-7.774
Jun	-8.492*	-9.738
Jul	-12.098*	-13.763
Aug	-12.994*	-14.876
Sep	-12.364*	-15.344
Oct	-5.680*	-9.405
Nov	-4.874*	-8.372
Constant	256.170*	15.091
R^2	0.746	
DW	2.287	
BP	8.971	

[a] The variables are defined as follows: w_1 = grower price, z_{11} = export price, z_{12} = processing price (apple juice), v_1 = harvesting labor wage rate, v_2 = price index of agricultural chemicals, v_3 = energy price index, v_4 = interest rate index, t = linear time trend. A single asterisk indicates significance at a 5% level.

Table 2. Apple Retail Demand Functions: 2SLS Estimates

	Market 1		Market 2		Market 3		Market 4		Market 5		Market 6	
Variable[a]	**Coeff.**	**t-ratio**	**Coeff.**	**t-ratio**	**Coeff.**	**t-ratio**	**Coeff.**	**t-ratio**	**Coeff.**	**t-ratio**	**Coeff.**	**t-ratio**
p_i / z_{21}	-0.073	-1.985	-0.147*	-13.570	-0.951*	-5.621	-0.162*	-8.373	-0.687*	-6.704	-0.358*	-9.932
z_{22}	0.131	1.433	0.229*	4.127	1.314*	3.968	0.137	1.783	0.850*	2.879	0.430*	2.951
z_{23}	0.005	0.711	0.001	0.342	0.042	1.532	0.007	1.529	0.023	0.774	-0.007	-0.786
z_{24}	0.017	0.877	0.031*	4.091	0.062	1.076	-0.013	-1.641	-0.017	-0.323	0.106*	4.785
z_{25}	-2.086	-0.994	0.222	0.724	-2.242	-0.499	1.038	0.909	12.607	0.974	-5.036*	-2.912
t	0.001	0.862	0.000	-0.942	0.001	0.488	0	-1.426	-0.002	-1.167	0.002*	2.726
Chain 2	-0.005	-0.812	0.033*	24.960	-0.035*	-3.237	0.031*	12.300	0.097*	6.444	0.138*	39.822
Chain 3	N.A.	N.A.	0.009*	5.241	-0.035*	-2.179	-0.034*	-12.160	0.054*	3.775	0.003	0.484
Chain 4	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	-0.039*	-8.626	0.102*	7.249	N.A.	N.A.
Chain 5	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	-0.081*	-13.090	N.A.	N.A.	N.A.	N.A.
Constant	0.703	0.993	-0.226	-0.889	1.057	0.457	-0.203	-0.553	-2.324	-0.942	2.009*	2.751
R^2	0.207		0.774		0.387		0.734		0.35		0.872	
DW	2.108		1.363		1.379		1.345		1.619		1.557	
BP	17.433		11.901		6.086		16.396		9.647		20.089	

[a] The variables are defined as follows: p_i = retail price, z_{21} = personal disposable income, z_{22} = retail price of bananas, z_{23} = retail price of table grapes, z_{24} = retail price of fresh oranges, z_{25} = personal disposable income per capita, t = linear time trend. Note: Jan. - Nov. dummy variable estimates are suppressed for presentation purposes. All Durbin-Watson tests fall in the inconclusive range. Critical chi-square values for the BP test at 5% and 15, 16, 17, and 18 df are 24.996, 26.296, 27.687, and 28.869, respectively. Therefore, we fail to reject the null hypothesis of no heteroscedasticity in each case. A single asterisk indicates significance at a 5% level.

Table 3. Summary of Apple Conduct Parameter Estimates

Market: Chain[a]	δ_0	δ_1	Total θ	τ_0	τ_1	Total ϕ	Weight	Wolfe χ^2
Northeast: 1	1.008* (22.184)	-0.007* (-6.585)	0.656* (24.295)	0.091 (1.429)	-0.001 (-0.615)	0.057* (2.246)	0.653* (11.407)	55.607
Northeast: 2	1.064* (2.901)	-0.011* (-2.416)	0.508* (2.461)	1.813* (9.005)	-0.011* (-3.001)	1.279* (10.018)	0.469* (5.728)	61.841
Atlantic Coast: 1	0.453* (2.845)	0.001 (0.683)	0.519* (5.217)	0.376 (0.707)	0.012 (1.573)	0.973* (5.166)	0.734* (12.086)	50.243
Atlantic Coast: 2	0.219* (3.244)	-0.004* (-4.710)	0.033 (0.963)	0.983* (25.864)	-0.006* (-12.097)	0.676* (37.484)	0.412* (6.004)	80.032
Atlantic Coast: 3	1.943 (1.903)	-0.056* (-3.242)	0.776* (2.174)	6.609* (5.979)	-0.084* (-4.885)	1.524* (7.336)	0.794* (14.803)	128.429
Midwest: 1	0.599* (9.104)	0.002* (2.097)	0.685* (19.270)	-0.385* (-23.411)	0.007* (23.752)	0.033* (5.510)	0.727* (13.508)	57.846
Midwest: 2	0.402* (3.633)	-0.002 (-1.053)	0.325* (5.193)	0.099 (1.029)	-0.001 (-0.521)	0.061 (1.032)	0.668* (8.469)	65.927
Midwest: 3	1.135* (28.278)	-0.019* (-38.577)	0.239* (11.422)	0.035* (7.783)	-0.001* (-12.360)	0.006* (4.407)	0.839* (22.287)	123.958
Southwest: 1	0.573* (2.266)	-0.006 (-1.652)	0.277* (2.544)	0.207 (1.689)	0.001 (0.041)	0.210* (5.169)	0.338* (5.011)	85.944
Southwest: 2	0.036 (1.161)	0.001 (1.197)	0.059* (4.041)	0.116* (19.097)	-0.001* (-4.709)	0.096* (40.822)	0.754* (16.063)	66.418
Southwest: 3	-0.156 (-0.798)	0.003 (0.944)	0.016 (0.213)	0.831* (6.139)	-0.001 (-0.253)	0.806* (12.617)	0.624* (9.449)	62.43
Southwest: 4	0.432 (1.152)	-0.003 (-0.776)	0.243 (1.237)	0.357* (2.316)	-0.002 (-1.082)	0.251* (2.714)	0.396* (5.001)	48.584
Southwest: 5	0.236 (0.099)	-0.002 (-0.069)	0.125 (0.094)	0.611 (0.521)	0.002 (0.119)	0.714 (1.528)	0.641* (5.996)	53.879
West: 1	0.535* (4.181)	-0.001 (-0.759)	0.468* (6.391)	-0.014 (-0.337)	0.001* (2.019)	0.052* (3.918)	0.234* (4.120)	111.133
West: 2	4.685* (8.542)	-0.065* (-8.323)	1.562* (6.718)	0.461* (8.373)	-0.006* (-6.084)	0.157* (18.957)	0.809* (16.329)	136.696
West: 3	0.614* (6.807)	-0.007* (-5.501)	0.265* (5.502)	0.145* (5.790)	-0.002* (-5.466)	0.039* (5.984)	0.131* (21.175)	132.817
West: 4	-0.832 (-1.934)	0.014 (0.221)	0.764* (3.977)	0.090 (1.122)	-0.001 (-0.741)	0.033* (2.847)	0.659* (10.129)	67.2
Southeast: 1	0.215 (0.348)	0.003 (0.394)	0.382 (1.243)	0.256 (0.424)	0.010 (1.313)	0.761* (2.458)	0.487* (6.394)	58.692
Southeast: 2	0.644* (2.723)	-0.010* (-2.768)	0.162 (1.426)	0.425* (9.371)	-0.003* (-5.328)	0.269* (11.085)	0.569* (7.256)	37.359

Southeast: 3	0.409	0.001	0.427*	0.294*	-0.002	0.171*	0.591*	59.843
	(1.394)	(0.087)	(3.497)	(3.436)	(-1.802)	(3.820)	(8.191)	

[a] The market power parameters are defined by the linear specifications: $\theta = \delta_0 + \delta_1 q_i$, on the buying side, and $\phi = \tau_0 + \tau_1 q_i$ in the output market for the collusive regime only. For Wolfe's test, the critical chi-square value at 5% and twelve degrees of freedom is 21.026. For all other variables, t-statistics are in parentheses. A single asterisk indicates significance at a 5% level. In this table, the "weight" parameter is interpreted as the percentage of observations observed in a cooperative phase.

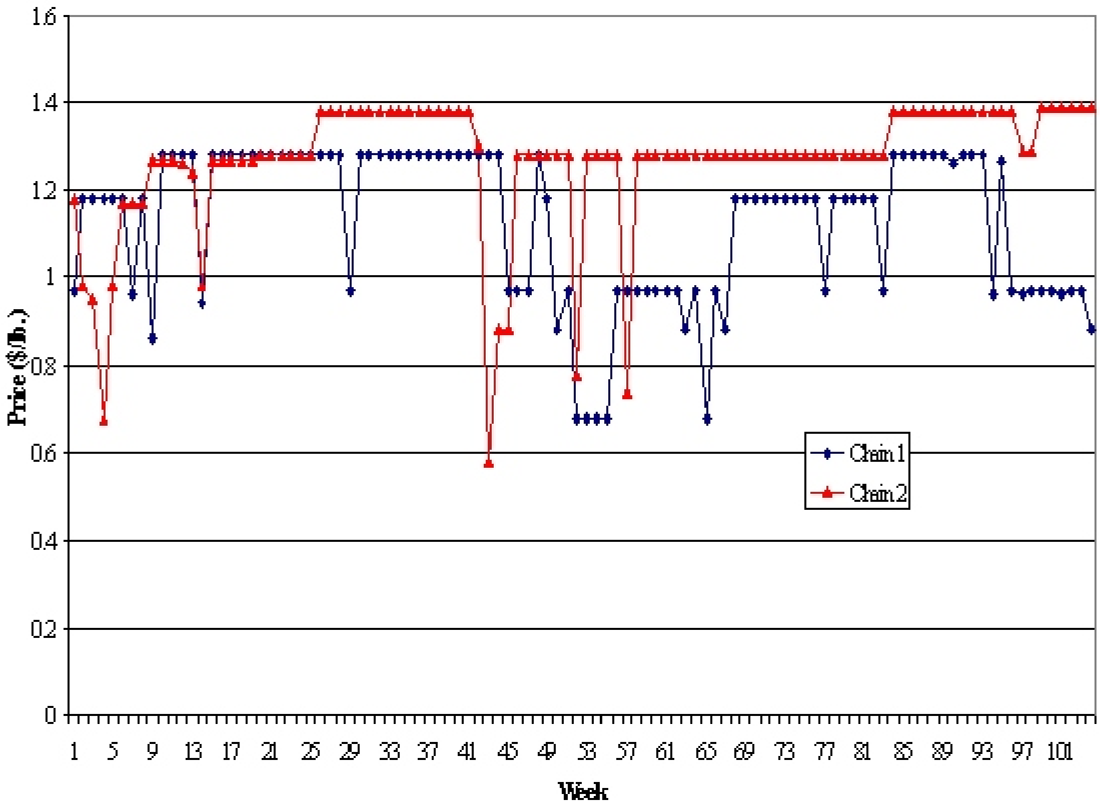

Figure 1 Red Delicious Apple Prices: January 1, 1998 - January 1, 2000