Technical Appendix

Appendix 1. Econometric Model of Tacit Collusion

Formally, assume a firm maximizes the present value of its expected future profits given an infinite series of input price strategies with the t element given by: wit.= sit (x0,x1,...,xt-1), so the objective function becomes:

$$V_1(\mathbf{s}_1) = \max_{si} E[\sum_{t=0}^{\infty} \beta^1 \pi_1(\mathbf{s}_1, s_{-1})] \tag{1}$$

for a set of rival strategies $\boldsymbol{s_{-i}}$, a discount factor $\exists^t$, and input prices w_t. Further, assume that the observed price is the realization of a random market price variable subject to a multiplicative disturbance: $w_t = \psi_t w(\sum_i x_{it})$, where P are i.i.d with continuous density f and distribution function F. 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.[1] 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 industry reversion to Bertrand prices:

$$V_1(w^i) > \pi_i\ (w^* + \beta^t V_i(z^i) \tag{2}$$

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 – the market price. Consequently, a discontinuous pricing strategy results depending upon the relationship between market prices observed in the previous period and a trigger price $\overline{w}$:

$$w_{it} = \begin{bmatrix} w_{it}, & w_{t\text{-}1} > \overline{w}, \\ z_{it}, & w_{t\text{-}1} < \overline{w} \end{bmatrix}. \tag{3}$$

Stanford shows that such discontinuous strategies are necessary to support subgame perfect collusive equilibria except in the trivial case where continuous reactions specify replication of the Nash component game outcome.[2] However, within the 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:

$$V_i(w_i) = \pi_i(w_i) + \beta \Pr(\overline{w} < \psi w) V_i(w_i) + \Pr(\overline{w} \geq \psi w)[\sum_{t=1}^{T-1} \beta^t \pi_i(z_i) + \beta^T V_i(w_i)], \tag{4}$$

[1] 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.

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

for reversionary periods of length T. Recognizing that $\Pr(\psi w_i < \overline{w}) = F(\overline{w} / w(w_i))$, (4) can be rewritten as:

$$V_i(w_i) = \frac{\pi_i(w_i) - \pi_i(z_i)}{1 - \beta + (\beta - \beta^T)F} + \frac{\pi_i(z_i)}{1 - \beta}, \tag{5}$$

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, requires the following first order condition to hold:

$$V_i(w_i) = \pi_i'(w_i)[1 - \beta + (\beta - \beta^T)\mathrm{F}] + (\pi_i(w_i) - \pi_i(z_i))[(\beta - \beta^T) f(\partial F / \partial s^i)] = 0, \tag{6}$$

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 this increase in input prices 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. In a repeated-game context, however, firms often have both the ability and incentive to renegotiate new equilibrium in order to avoid the punishment phase. Farrell and Maskin are among authors who show that renegotiation reduces the likelihood of observing an effective trigger-price equilibrium, but this ability again depends on the structure of the industry and the nature of rival interactions. Clearly, however, determining whether or not the data are consistent with this conceptual pricing model requires an empirical approach that is able to identify both the exercise of market power during collusive regimes, and the endogenous switch to periods where firms price competitively.

A general model of processor profit maximization under imperfect competition forms the basis for estimating an econometric model of shipper- and retail-level produce price determination. However, given the relationships between buyers and sellers, and among buyers themselves described above the usual approach to modeling Bertrand rivalry must be extended to allow the dynamic Nash behavior described above. Namely, this model must account for the possibility that observed behavior, and the estimated market power parameters, vary both over time and discontinuously by behavioral regime. At the core of the model presented by Green and Porter lies a familiar conduct mechanism similar to that developed by Appelbaum; Bresnahan; or Lau. Our extension to this approach involves estimating endogenous switch points within the sample period that delineate competitive from cooperative periods.

Estimating a model with discontinuous regimes of market power requires the ability to identify two sets of conduct parameters where the switching behavior between the two is determined endogenously. Due to this endogeneity, the switching points between regimes are unidentifiable, or latent quantities. Consequently, this study uses an empirical approach that is able to identify both the degree of market power exercised in each regime and switching points between regimes. To do so, we use a finite mixture estimation (FME) model (Titterington, Smith, and Makov) and estimate it using an expectation / maximization (EM) algorithm (Dempster, Laird, and Rubin). The logic behind this approach is straightfor-

ward and well understood in the literature. Further, in order to separate the exercise of market power from the impact of changing supply and demand on produce margins, we develop a model of price determination within each regime of punishment or collusion.

Assume that the produce-retailing industry consists of N firms, all selling a product that is differentiated on the basis of a quality reputation, a market location, or by providing associated retail services to its customers. Further assume that these retailers convert produce at the farm level to saleable goods using the same, fixed proportions technology, herein assumed to be one-for-one without loss of generality. This assumption means that raw inputs are separable from other, non-farm inputs. To simplify notation, assume the production technology can be written as: $x_{ij} = \lambda_{ij} q_{ij}$ 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 8_{ij} is a constant of proportionality, assumed here to be 1.

To allow for grower reputations for quality, or simply for the value of relationship-buying among retail agents, the model is cast in a differentiated-product framework where an individual seller's price is allowed to differ from an industry-wide average price. Assuming retailer i receives a price $p_{ij}\,(X_j(W_j, z_2), z_1)$ where $\boldsymbol{z_1}$ is a vector of demand-shifting exogenous variables, $\boldsymbol{z_2}$ is a vector of supply-shifting exogenous variables and W is the industry-wide grower price. Assume each retailer pays its suppliers a price w_{ij} for x_i pounds of produce of type $j\,(X_j = \sum_i x_{ij} \forall j)$ and that the cost of selling produce can be described by a cost function that is separable between buying and selling activities, so that the retailers' profit maximization problem is:

$$\max_{wi}[\pi_i] = \max_{wi}\,[(p_i - w_i)x_i(W) - C(x_i(W), \mathbf{v}]\forall j \in J. \tag{7}$$

Interpreting $x_j(W_j, \boldsymbol{z_2})$ as the supply curve facing each retailer for each commodity, and $p_j(X_j, \boldsymbol{z_1})$ as the inverse retail demand curve - again specific to each seller - and $C(x_i(w_i), \mathbf{v})$ as total cost, a representative retailer's first order condition becomes:

$$\frac{\partial \pi_i}{\partial w_i} = (p_i - w_i)\frac{\partial p_i}{\partial W}\frac{\partial W}{\partial w_i} - x_i(W) + x_i(W)\frac{\partial p_i}{\partial X}\frac{\partial X}{\partial x_i}\frac{\partial x_i}{\partial W}\frac{\partial W}{\partial w_i} - \frac{\partial C}{\partial x_i}\frac{\partial x_i}{\partial W}\frac{\partial W}{\partial w_i} = 0 \tag{8}$$

for each commodity, suppressing the j subscript. Because our data is specific to each retailer, we write firm-level margin equations in terms of supply- and demand-curve slopes and conjectures of both input and output market reactions for each commodity j as:

$$m_i = [p_i - w_i] = c_i + x_i(W)(\eta i \theta i)^{-1} - x_i(W)(\in_i \Phi_i), \tag{9}$$

where c_i is the marginal cost of marketing for firm i, $\mathbf{0}_i$ is the slope of the supply curve facing each firm, 2_i is firm i's conjecture of how the input market price changes for a one unit change in the price it pays, ,i is the slope of each firm's perceived inverse retail demand function, and N_i is the firm-specific conjectural variation in output quantities. Equation (9) is simply a statement of the condition for optimal input employment by a firm with oligopsony and oligopoly power -- that the marginal value product for each input is set equal to its marginal outlay. Whereas the conduct parameter, or conjecture, is typically interpreted as parameterizing the degree of market power, in this application it is more general in that it

describes the extent to which conduct is bounded away from perfect competition given that the industry is in a stage of non-cooperative behavior.[3] In order to identify this parameter, however, it is necessary to impose additional restrictions on the slope of the supply curve, 0 and the demand curve, ,.

Typically, this is accomplished by simultaneously estimating input supply and output demand functions wherein their slopes are allowed to vary over time, or to rotate independent of price changes caused by the exercise of market power (Bresnahan). Therefore, input supply is estimated as a function of the grower price, an interaction term between price and another explanatory variable, and a set of other exogenous variables. A similar specification is used for the demand curve. Following Lau or Schroeter and Azzam, the supply curve is specified as a linear function of farm-level own-commodity prices and a set of exogenous factors such as input prices, weather-events, or prices of alternative crops:

$$X(w, z_2) = \alpha_o + \eta^{-1}(w / z_{2k}) + \sum_{i \neq j} \alpha_i z_{2i} + \mu_2, \tag{10}$$

whereas the inverse-demand curve is a function of industry quantity demanded and such demand-shifters as income, alternative commodity prices and seasonal dummy variables:

$$p(X, z_1) = \alpha_o + \in (X / z_{1k}) + \sum_{i \neq k} \alpha_i z_{1i} + \mu_3. \tag{11}$$

With weekly data, this model is estimated assuming fixed weekly effects as supply clearly differs due to seasonal factors. Moreover, we estimate both supply and demand models using two-stage least squares due to assumed endogeneity of grower prices and market demand, respectively. The results obtained by applying these two models to the apple, grape, grapefruit and orange data are found in tables 1 and 2 (apples), tables 4 and 5 (grapes), tables 7 and 8 (oranges) and tables 10 and 11 (grapefruit). For further interpretation of the results shown there, the interested reader is referred to Richards and Patterson (2001). Once the values of 0 and , are substituted into (9), an expression for retail produce marketing costs must be included prior to estimating the entire system.

From the class of flexible functional forms, Diewert's Generalized Leontief (GL) provides several favorable characteristics for the cost function: it is inherently homogeneous in prices without normalization, it is affine in output without further restriction, and it imposes convexity in output, while concavity in prices, symmetry, and monotonicity can be maintained and tested. For a single output (q) and m input prices (vi), the GL cost function becomes:

$$c(x, \mathbf{v}) = x \sum_i \sum_j \gamma_{ij} (v_i v_j)^{1/2} + x^2 \sum_i \gamma_i v_i + \mu_1, \tag{12}$$

[3] There is considerable debate on the interpretation of these parameters in the literature. Appelbaum maintains that if 2 = 1 and N = 1, then a retailer behaves as if it is a monopsonist in the input market and a monopolist in the output market, respectively, while if 2 = 0 and N = 0, it behaves as if both the input and output markets are perfectly competitive. However, in a homogeneous product oligopsony with *N* firms it can be shown that 2 is bound by 1/*N* (which implies that 2 goes to zero as *N* becomes large) and 1 if the market price is regarded as an average over all firms' individual prices. On the other hand, N is instead bound by [0, *N*] under these same assumptions. We thank Rich Sexton for these insights.

where $:_1$ 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. With this specification, derivation of the associated marginal cost function is straightforward. While this model allows the elasticity of supply to vary over time, it is also common to assume that the conduct parameter may also vary with various aspects of the economic environment (Schroeter and Azzam, for example). This is particularly important in our case in order to test the hypothesis that retailer market power falls in the level of fresh produce shipments.

In a more general sense, there may be other factors that influence the exercise of market power. Therefore, define ***K*** as a vector of economic factors that are likely to influence the degree of market power. In particular, if reliable data on concentration levels, barriers to entry or other structural indicators were available on a more frequent basis, then we could directly test the hypothesis that certain structural features may contribute to a retailer's ability to use market power. Limiting the model to the existing data, however, each market power parameter can be written as a linear function of quantity:

$$\begin{aligned} \theta(X|\delta) &= \delta_o + \delta_1(X) + \mu_{4,} \\ \phi(X|\tau) &= \tau_1(x) + \mu_5. \end{aligned} \tag{13}$$

Although it is common practice to estimate equations (9) - (12) simultaneously, this study estimates raw product supply, retail demand and the fresh produce margin equations sequentially due to the added complexity of the multiple-regime finite mixture model.[4] The logic underlying this model and its value in estimating multiple market-power regimes are outlined in the following section.

[4] Sequential estimation produces parameter estimates that are consistent, but inefficient relative to those found with a full-information estimator such as FIML or 3SLS.

Appendix 2. Finite Mixture Estimation of Switching Regressions Model

Essentially, the FME approach maintains that observations of the dependent variable, retail-shipper margins in the current case, are not drawn from one distribution, but rather two 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:

$$f_i(m_i) = \rho_i f_{1i}(m) + \ldots + \rho_k f_{ki}(m_i) \tag{14}$$

where the mixing weights are defined as $\rho_j > 0, \sum_j \rho_j = 1, j = 1,2,\ldots,k$ and the individual densities must, of course, meet the restrictions that: $f_i(> 0, \int f_j(m_i)dm = 1$ 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 commodity margins are normally distributed, and simplifying the mixture distribution to represent only two regimes, the density can be written as:

$$f_i(m_i \mid \Omega) = \rho(m_i \mid \mu_1, \sigma) + (1 - \rho)\psi(m_i \mid \mu_2, \sigma), \tag{15}$$

where P is the normal density function, and $\mu_i = Z\alpha_i$ for regime i and a vector of explanatory variables, **Z**. Wolfe describes a modified likelihood ratio test that is typically used to test the null hypothesis of a two-regime model against a more restrictive single-regime alternative. Wolfe's test is an approximation to likelihood ratio test based on a modified Chi-square distribution with test statistic:

$$S = (2 / N)(n - 1 - d - (C_1 / 2)) \log L, \tag{16}$$

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 our case), and d is the dimension of the underlying normal distribution. The test statistic is Chi-square distributed under the null hypothesis with $2d\ (C_1 - 1)$ degrees of freedom. In terms of the produce buying market structure example, the two regimes are defined by differences in each element of their respective parameter vectors, but most importantly, by differences in the conjectural elasticity of input supply. Modifying equation (9) to be consistent with the switching-regression logic, the margin model becomes:

$$m_{i,t} = \begin{bmatrix} c_{i,t} & with prob. \rho \\ c_{i,t} + (\eta_{i,t}\theta_i)^{-1} x_{i,t} & with prob. (1 - \rho \end{bmatrix}, \tag{17}$$

for each commodity j. However, estimating (15) is not straightforward because the separation points between the two regimes are unobservable.

Unlike Porter (1983), who has data indicating, albeit imperfectly, periods of collusion among nineteenth century railways belonging to the Joint Executive Committee, no such data exists for this study. Therefore, the estimation technique must be able to infer an optimal mixing weight from the data that defines two distinct regimes that are relatively homogeneous within each, but significantly different between.[1] One such latent variable method is the expectation / maximiza-

[1] In this respect, FME is very similar to latent class and cluster analysis.