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Conduct of Firms in Dynamic U.S. Food Industries

A.J. Reed

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Abstract

This study describes a procedure that is used to identify firm conduct, or the nature of competition in three food markets. The procedure assumes food-producing firms incur short-run capital adjustment costs, and pursue unchanging conduct. The estimates, however, are consistent with firms altering their conduct as market conditions change.

Keywords: firm conduct, dynamic games, Bayesian bootstrap.

Contents

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Albert J. Reed

Introduction

The conduct of food-producing firms is central to a number of issues in food economics. If cooperative firms collude and 'unduly' enhance price, they may violate Capper-Volstead provisions. Claims of monopsonistic conduct among U.S. meatpacking firms have also led to a recent investigation (Commodity Futures Trading Commission, 1994). Also, the transmission of prices through the food system is influenced by competition in the food industry. In imperfectly competitive markets, retail prices may be higher and farm prices may be lower than in perfectly competitive markets.

Price distortions caused by imperfectly competitive food industries result from market inefficiency: output combinations (e.g., food-other goods, high-quality food--low quality food) can be rearranged so both consumers and food producers could be better off. Economists argue perfect competition ensures that buyers can be made no better off without making sellers worse off. The food industry's argument is different. If a firm in an imperfectly competitive industry acquires its market power *because* of cost advantages over smaller, competitive firms, eliminating the dominant firm's behavior might eliminate the cost advantages that reduce consumer prices. Both views are correct. Despite possibly lower prices offered by more cost efficient, dominant firms, output combinations of an imperfectly competitive industry could still be found that make both food producers and consumers better off.

Recent studies have argued that imperfect competition may explain current trends in the food industry. The view that vertical integration and contract production eliminates vertical externalities presumes not only that imperfect competition exists, but that it can be identified (Henderson, McCorriston, Sheldon, 1993; McCorriston and Sheldon, 1995). This paper presents a methodology for econometrically identifying the nature of competition in the food industry.

In this paper, firm conduct refers to the nature of competition, and describes the behavior of an optimizing firm in the presence of competing firms. The early studies by Appelbaum (1979,1982) make statistical inference about firm conduct using market-level data. To various degrees, the studies by Wohlgenant and Haidacher (1989), Holloway (1991), Schroeter and Azzam (1991), and Karp and Perloff (1993) draw on Appelbaum's approaches. Like the referenced works, the present study also draws on Appelbaum, but departs

See footnotes at the end of the report..

fundamentally from them in a number of ways.

The present study sympathizes with the argument that the nature of competition in food markets can be better understood in the context of economic growth and market expansion than it can in the usual textbook static model (Paul, 1974). The increased capitalization of meat-processing firms, for example, may have resulted in fewer firms, and may have been driven less by a desire to collude than by technical investments that alter the characteristics of final retail products (Drabenstott, 1994). The concept of capitalization fits more naturally into the dynamic frameworks of Schroeter and Azzam, and Karp and Perloff than it does in the static frameworks of Wohlgenant/Haidacher, and Holloway. The present work argues that beneath the changes in vertical coordination currently taking place in the food industry is a change in the flow of capital into the industry. This flow imparts changing dynamics to food prices, consumer expenditures, and other market indicators. It is within the context of a dynamic industry that this study attempts to identify competition.

In growing food markets, firms may adapt cost-saving technology or forge closer relationships with other firms without altering the nature of competition (Paul). An increase in industry concentration, for example, may grant firms little more control over market prices if a competitive fringe exists. Evidently, the biological advances adopted by the broiler industry during the 1950's and 1960's may have altered the industry from one characterized by atomistic firms and spot markets to one characterized by contract agriculture. Paul's point is that while a spot market may have disappeared, and the poultry industry is more concentrated than in the past, firms may still compete perfectly, perhaps for forward contracts. Ultimately, consumers benefit if firms in all industries reduce costs in perfectly competitive markets.

The three market equilibria presented below are derived from a single, structural economic model. They differ only with respect to firm conduct. The three systems define different relative degrees of correlation between the endogenous and the exogenous (time series) variables. The perfectly competitive (collusive) equilibrium exhibits the strongest (weakest) correlation of endogenous industry demand for farm ingredients, and of farm and consumer prices, with exogenous shifts in consumer demand. The Cournot-Nash equilibrium exhibits an intermediate level of correlation. The three systems also define different relative magnitudes of variability of endogenous price and quantity (time series) variables. The perfectly competitive (collusive) equilibrium generates the most (least) variable endogenous prices and quantities. Again, a Cournot-Nash equilibrium results in an intermediate level of variability. The single, econometric reduced-form exploits differences in the variability and correlation of sample data to pin down one equilibrium and to identify firm conduct.

The estimates are also used to analyze the effect of consumers on the performance of the food industry. Changing demographics, and changing preferences for safe and convenient food may have transformed the consumer to become less price sensitive than in the past (Thurman, 1986; Kinsey, 1994). Paul finds it perplexing that, in competitive markets with price inelastic consumers, food firms would undertake significant investment when they are vulnerable to unstable returns. The analysis below reveals that because rational firms predict consumer prices using consumer demand functions, it is optimal to reduce supply adjustments in inelastic markets to offset market fluctuations.

Paul's arguments suggest that, as technology changes, or as firms enter an industry, or as relationships between firms change, the true structure and conduct parameters of an economic model change. Industrial organization studies recognize this and often focus on the relationship between an industry's changing structure and its changing conduct. Bayesian inference, in contrast to classical inference, assumes that a model's true structure and conduct parameters change; they are considered random variables that follow a fixed distribution. Different draws from the distribution of parameters might be conceptualized as different organizations of a market. Rather than impose *ad hoc* or unreasonable relationships between conduct and structure, the Bayesian approach allows one to measure the covariance between the true conduct and structure parameters.

The Economic Model

The economic model consists of a dynamic and stochastic objective function of a representative food processing firm, a consumer demand-for-food function, a commodity supply function, and exogenous demand and supply shifters. The solution of

$$V_o = \max_{\{f_t\}} \mathscr{E}_o \sum_{t=o}^{\infty} \beta^t \{p_t \phi f_t - w_t f_t - \frac{h}{2} f_t^2 - \frac{d}{2}(f_t - f_{t-1})^2\} \qquad (1)$$

subject to

$$p_t = -A\phi F_t + u_t \quad (\textit{Consumer demand}) \qquad (2)$$

$$w_t = B_o + B_1 F_t + \epsilon_{1t} \quad (\textit{Commodity supply}) \qquad (3)$$

$$u_{t+1} = \rho_o + \rho_1 u_t + \epsilon_{2t+1} \quad (\textit{Consumer demand shifts}) \qquad (4)$$

is used to make inferences on conduct in the food processing sector.

Equation 1 is the objective function of a representative food processing firm. Equation 1 states that the firm chooses the level of farm input, f_t, to process in each period t so that over the infinite time horizon, it will have chosen the sequence, $\{f_t\}$, that maximizes expected value. Each firm receives the consumer price, p_t, for each unit of food produced in period t, and pays the farm price, w_t, for each unit of farm ingredient purchased in period t. There are, effectively, n firms in the market so F_t is the market level of farm ingredient processed in period t (i.e., F_t=n f_t). Equation 2 is the consumer-demand function for food, equation 3 is the commodity-supply function for farm ingredient, and equation 4 is the motion equation describing the distribution of consumer demand shifts. The parameters of equations 1 to 4 are the structural parameters of a hypothetical food market.

The structural parameters of equation 1 describe the technology of representative food processing firms. The parameter ϕ is the processor's food-output--farm-input parameter, and β (= 1/(1+r), where r is the nominal interest rate) is the firm's discount factor. The h parameter defines steady-state costs associated with the scale of production. The term $(h/2)f_t^2$ denotes the capital consumed to maintain a level of production. h>0 denotes increasing steady-state costs, as more capital is consumed with increased levels of processing. h<0 defines decreasing and h=0 defines constant, steady-state costs.

One way to motivate the cost-of-adjustment function, $\frac{d}{2}(f_t - f_{t-1})^2$, is to consider the role capital plays in coordinating the movement of the farm commodity through the marketing system. It is often thought that firms realize economies when they switch from open production (i.e., spot markets) to contract production or vertical integration. This study argues that such arrangements reflect a coordination of capital between firms operating at different stages of food production. Firms realize economies when they arrange capital so that the minimum average cost of production at one stage corresponds to the minimum average cost level of production at another stage (Mighell and Jones, 1963).

As an example, consider a processing firm that is independent of a wholesaling firm. The processing firm purchases a quantity of farm commodity, f, and transforms it into a processed food product in period t. In doing so, the processor consumes both physical capital (e.g., machines, plant, equipment), and human capital (e.g., management). Denote the cost of the capital consumed at the processing stage in period t as $s_{1t} = (\delta_1 f_t)^2$. Once processed, the product is transported to the assembly or wholesale plant where it is assembled, packaged, and labeled in the next period, t+1. Suppose the capital cost at the wholesaling stage is $s_{2t+1} = (\delta_2 f_t)^2$. The time delay constrains the firm to wholesale only processed products. Both cost functions exhibit diminishing returns to capital.

If the firms are independent, processors might sell their output on the open market, and the capital cost of processing and wholesaling is $s_{1t} + s_{2t}$ in period t. If, however, the firms negotiate a contract with each other, or vertically integrate their stages, they have an incentive to coordinate their capital to achieve greater control and realize cost efficiencies. Denote the cost economy as $\kappa(s_{1t}, s_{2t}) = h(s_{1t} s_{2t}) = g f_t f_{t-1}$, so the total capital cost of processing and wholesaling is $s_{1t} + s_{2t} - \kappa(s_{1t}, s_{2t}) = \delta_1^2 f_t + \delta_2^2 f_{t-1} - g f_t f_{t-1}$. These ideas are incorporated into the model if $\delta_1^2 = \delta_2^2 = d/2$, and $g = d$.

Finally, the A_1 and B_1 parameters of equations 2 and 3 are slope parameters of the consumer demand and farm supply functions. Roughly, small values of B_1 are associated with farm-price-responsive producers, and small values of A_1 are associated with retail-price-responsive consumers.

The market-clearing solution to equations 1 to 3:

$$F_t = \lambda F_{t-1} + \left(\frac{\lambda}{(d/n)}\right)\{\phi u_t + \phi(\beta\lambda\rho)\mathscr{E}_t u_{t+1} + \phi(\beta\lambda\rho)^2\mathscr{E}_t u_{t+2} + \ldots\}, \qquad (5)$$

links the structural parameters of firms and consumers to the distribution of industry-level demand for farm output. Equation 5 states that the aggregate level of farm input processed in any period t is related to last period's input, and to the current and expected discounted future stream of consumer demand shifts.

The magnitude of the feedback coefficient, λ, in equation 5 largely determines both the variance of $\{F_t\}$ as well as its lagged covariance. If $\{F_t\}$ is stable, λ is less than one in magnitude, so that following a disturbance, the series will "step" toward steady-state if it is not disturbed further. The magnitude of the 'step-size', $F_t - F_{t-1}$, and the speed at which a series reaches steady state is directly related to λ. Large steps characterize series with a large, one-period-lagged covariance. $\{F_t\}$ is said to be resistant to change if , when disturbed from steady state, it returns quickly to steady state by taking 'large' steps. Conversely, series with small, one- period- lagged covariance are associated with values of λ close to zero, and that take small steps toward steady state. Furthermore, large values of λ imply a large variance of $\{F_t\}$, and small values of λ imply a small variance of $\{F_t\}$.

The above arguments contradict a textbook static market model which suggests price fluctuations increase as the elasticity of demand and supply schedules decrease. In the model presented above, the magnitude of λ is negatively related to the magnitude of the A_1 or B_1 parameters. A_1 and B_1 represent, roughly, inverse price elasticities, and their negative relationship indicates that, as consumers and primary producers become less price elastic, the variability of market-clearing prices diminishes. The static textbook result has led some to question why firms that operate in inelastic food markets and face volatile returns would choose to increase investment (Paul). Furthermore, consumer substitution toward more highly processed foods may decrease the elasticity of the market-level derived demand facing food industries (Thurman) and, according to the textbook view, increase the volatility of food markets.

In contrast to the static theory, the theory appealed to here claims firms use all available information in making predictions. According to this view, food-producing firms base predictions on their knowledge of consumer preferences and on the state of farm markets. Analytically, the A_1 and the B_1 coefficients enter the optimal prediction formulas. In inelastic markets, firms have an incentive to reduce the variability of their supply moreso than in elastic markets to avoid higher capital adjustment costs in a potentially more volatile market.

The theory could be used to measure consumer and farm producer contribution to market volatility. The feedback parameter, λ, is inversely related to the consumer ratio, $A_1/(d/n)$, and inversely related to the farm- producer ratio, $B_1/(d/n)$. Values of λ, $A_1/(d/n)$, and $B_1/(d/n)$ are comparable both within and across industries. If $A_1/(d/n)$ exceeds $B_1/(d/n)$ in the pork industry, one could infer that the fluctuation of market indicators is driven primarily by consumers, rather than by farm producers. Cross-industry comparisons could also be made. If sorting industries by increasing magnitudes of $A_1/(d/n)$ matches the sorting by decreasing magnitudes of λ, one might conclude that consumers dominate data fluctuations among the industry groups. On the other hand, if sorting industries by increasing magnitudes of $B_1/(d/n)$ matches sorting industries by decreasing magnitudes of λ, one might conclude that producers dominate data fluctuations among the groups.

The theory also characterizes the responsiveness, or the correlation, between endogenous prices or quantities and shifts in consumer demand. The coefficient $\lambda/(d/n)$ in equation 5 measures the strength of firms' and markets' responses to the expected future stream of consumer demand shifts. Theory indicates $\lambda/(d/n)$ is inversely related to (d/n), (h/n), A_1, or B_1. As firms realize reduced costs of adjustment, or scale economies, or as consumers or producers become *more* price responsive, firms and markets exhibit a greater response to consumers. However, if food markets are characterized by *less* price responsive consumers and by reduced cost of capital adjustment, the strength of an industry's response to shifts in consumer demand is ambiguous.

The probability laws governing consumer demand and commodity supply shift sequences, $\{u_t\}$ and $\{\epsilon_{1t}\}$, also contribute to the fluctuation of market data. A value of ρ_1 near 1 in magnitude in equation 4 describes a consumer demand shift series that is "permanent" and resistant to change, and a value near 0 describes a transitory series that is adaptable to change. For convenience, the farm supply shift series, $\{\epsilon_{1t}\}$, is assumed to be a white noise or a completely transitory series. The empirical representation of equation 5 can be computed only after the distribution of $\{u_t\}$ and $\{\epsilon_{1t}\}$ has been specified.

$\mathscr{E}_t$ is a mathematical expectations operator taken with respect to firms' subjective distribution of relevant economic variables, and conditioned on firms' information set in period t.[2] Furthermore, firms' subjective probability distributions are equivalent to the actual probability laws generating the data. In short, firms are assumed to form rational expectations. The rational expectation solution (Sargent, 1989, Ch. 9) is

$$F_t = \kappa_o + \lambda F_{t-1} + \left(\frac{\lambda}{(d/n)(1-\rho_1\lambda\beta)} \right) \phi u_t \quad (6)$$

where

$$\kappa_o = \frac{\lambda^2 \phi \rho_o \beta - \lambda B_o (1 - \lambda \beta \rho_1)}{(d/n)(1 - \lambda \beta \rho_1)(1 - \lambda \beta)}.$$

Equation 6 is the market-clearing, reduced-form solution of commodity processed into food, and represents a well-defined, rational expectations equilibrium.[3] Unlike equation 5, equation 6 is observable, and equations 4 and 6 form an econometric model.

Econometric estimates of the parameters of equations 4 and 6 can be used to identify a conduct parameter, and to make inference on the nature of competition. Understanding the connection between the econometric representation and conduct requires a comparison of the necessary condition of equation 1, or the Euler equations, under perfectly competitive, perfectly collusive, and oligopolistic arrangements.

Perfect Competition

The Euler equations

$$\phi p_t = w_t + \beta d\{r[f_t - f_{t-1}] - [(\mathscr{E}_t f_{t+1} - f_t) - (f_t - f_{t-1})]\} \qquad t = 1,2,\ldots .$$

associated with equation 1 represent necessary conditions of a representative firm buying farm commodities and producing food output in a perfectly competitive market. The term on the left is the marginal value product, and the term on the right is the marginal cost of producing one unit of food. Marginal costs consist of payments to commodity suppliers and a user cost of capital. The user cost consists of the interest cost forgone by investing in a unit of capital, $rd(f_t - f_{t-1})$, less current period capital gains, $d(\mathscr{E}f_{t+1} - f_t) - d(f_t - f_{t-1})$. Capital gains accrue if the current period fluctuation in production is less than next period's expected fluctuation. Aggregating the Euler equations over identical firms, imposing market clearing, and expressing the result in terms of industry aggregates gives[4]

$$(d/n)\beta z^{-1} - \Theta_{pc} + (d/n)z = 0 \qquad (7)$$

where $\Theta_{pc} = \phi^2 A_1 + B_1 + (d/n)(1 + \beta)$. Equation 7 is the characteristic equation of a perfectly competitive industry. The inverse of z that solves equation 7 is the value of λ for firms in a perfectly competitive industry.

Perfect Collusion

The Euler equations

$$\phi(p_t - A_1 \phi F_t) = (w_t + B_1 F_t) + \beta d\{r[f_t - f_{t-1}] - [(\mathscr{E}_t f_{t+1} - f_t) - (f_t - f_{t-1})]\} \qquad t = 1,2,\ldots .$$

associated with equation 1 represent necessary conditions of a representative firm in perfectly collusive input and output markets. The above Euler equations assume that each firm cooperates with other firms in setting output. In the case of identical firms, cooperation means each firm produces the same output level. The term on the left is the marginal revenue product, and the first term on the right represents payments to commodity suppliers. The term $A_1\phi F_t + B_1F_t$ is the penalty paid by food consumers and commodity producers to the food processing firm because it colludes. $A_1\phi F_t + B_1 F_t$ represents society's marginal gain if the industry were perfectly competitive. Aggregating over identical firms gives

$$(d/n)\beta z^{-1} - \Theta_m + (d/n)z = 0 \qquad (8)$$

where $\Theta_m = 2(\phi^2 A_1 + B_1) + (d/n)(1+\beta)$. Equation 8 is the characteristic equation of a perfectly collusive industry. The inverse of z that solves equation 8 is the value of λ for perfectly collusive firms.

Cournot-Nash Oligopoly

The Euler equations

$$\phi(p_t - A_1\phi f_t^{(j)}) = (w_t + B_1 f_t^{(j)}) + \beta d\{r[f_t^{(j)} - f_{t-1}^{(j)}] - [(\mathscr{E}f_{t+1}^{(j)} - f_t^{(j)}) - (f_t^{(j)} - f_{t-1}^{(j)})]\}$$

associated with equation 1 represent necessary conditions of the jth representative firm in Cournot input and output markets. The above conditions state that the jth firm does not cooperate with competing firms and assumes that the competing firms will not respond, in the current period, to the jth firm's decision in the current period. The term on the left represents the marginal revenue product, and the first term on the right represents payments to suppliers. The term $A_1\phi f_t^{(j)} + B_1 f_t^{(j)}$ represents the (marginal) penalty that food consumers and commodity suppliers pay to firm j because of Cournot-Nash competition. Aggregating gives

$$(d/n)\beta z^{-1} - \Theta_o + (d/n)z = 0. \qquad (9)$$

where $\Theta_o = \frac{n+1}{n}(\phi^2 A_1 + B_1) + (d/n)(1+\beta)$. Equation 9 is the characteristic equation of a Cournot oligopoly. The value of the inverse of z that solves equation 9 is the value of λ for the Cournot oligopolist.

Equations 7 to 9 are used to identify conduct, and reveal the role conduct plays in determining the variability of market-level data. Notice the definition of Θ_{pc} in equation 7, Θ_m in equation 8, and Θ_o in equation 9. If $(n+1)/n \rightarrow 1$, $\Theta_o = \Theta_{pc}$, and an infinite number of firms compete in a perfectly competitive industry. If (n+1)/n→2, $\Theta_o = \Theta_m$, and firms collude and act as a single firm. Furthermore, equation 9 reveals that (n+1)/n has the same effect on the feedback parameter, λ, as do the parameters A_1 and B_1. From the above results, it follows that perfectly competitive conduct leads to the greatest variability of market indicators and to the largest market response to shifts in consumer demand. Collusive conduct leads to the least variable market data, and to the smallest response to shifts in consumer demand.

Statistical inference on conduct and on the other parameters is computed by conditioning econometric estimates of some parameters on fixed values of other parameters. In this case,

estimates of $\Theta = \left[\frac{n+1}{n},(d/n),\rho_1,\kappa_o,\rho_o\right]$ are conditioned on fixed values of

$\omega = [\beta,\phi,h,A_1,B_1]$ using market-level data, and the statistical representation

$$F_t = \kappa_o + \lambda F_{t-1} + \left(\frac{\lambda}{(d/n)(1-\rho_1\lambda\beta)}\right)\phi u_t + e_t \qquad (11)$$

$$u_{t+1} = \rho_o + \rho_1 u_t + \epsilon_{2t+1}. \qquad (4)$$

$\{F_t\}$ and where $\lambda = \lambda\left(\frac{n+1}{n},(d/n),\omega\right)$ highlights the notion that λ is explicitly solved from

characteristic equation 9. Estimates of (n+1)/n "close" to 1 indicate conduct is "close" to perfectly competitive; estimates between 1 and 2 indicate a Cournot-Nash oligopoly; and estimates close to 2 indicate that conduct is close to perfectly collusive. Estimates of (n+1)/n outside [1,2] suggest a non-cooperative oligopoly in which firms account for current period reaction of competing firms. The next section provides more details into transforming data, conditioning the parameters, and explaining the method of statistical inference.

Empirical Analysis

The above discussion suggests that statistical inference on firm conduct centers on estimates of the (n+1)/n parameter. Classical inference might use the point estimate of (n+1)/n to refute the null hypothesis that (n+1)/n equals 1.[5] Failure to reject this hypothesis provides evidence of perfect competition. Classical inference might also use the point estimate to refute the null hypothesis that (n+1)/n equals 2. Failure to reject this hypothesis provides evidence of perfect collusion. Similarly, classical inference might use the point estimate to refute the null hypothesis that 1.0 < (n+1)/n < 2.0. Failure to reject this hypothesis provides evidence of Cournot-Nash oligopoly. Rejecting all three hypotheses might serve as evidence of more complex conduct. The problem occurs when all three hypotheses cannot be rejected.

An alternative procedure is implemented in this study. The procedure amounts to setting up fixed and mutually exclusive intervals for the (n+1)/n parameter that are centered around 1 for perfect competition, around 1.5 for Cournot-Nash, and around 2 for perfect collusion. The intervals chosen in this study are:

$$\textit{Perfect Competition}: \quad 0.95 \leq \frac{n+1}{n} \leq 1.05$$

$$\textit{Perfect Collusion}: \quad 1.95 \leq \frac{n+1}{n} \leq 2.05$$

$$\textit{Cournot}: \quad 1.05 \leq \frac{n+1}{n} \leq 1.95$$

Inference is obtained by finding the interval with the largest number of draws. The procedure treats (n+1)/n and the other estimated parameters as random variables, and computes the multivariate distribution function. In short, the procedure is Bayesian.

In Bayesian inference, the posterior probability function represents the joint distribution function of a model's true parameters. The goal of Bayesian inference is to compute or summarize the posterior. Formally, the posterior is the product of the likelihood and the prior. Under the assumption of a quadratic-loss function, the mean of the posterior represents the point estimate of the parameters that minimize the loss function, and the standard deviation of the posterior provides a measure of parameter dispersion. The covariance of the posterior could be used to measure the link between parameters that describe conduct (i.e., (n+1)/n), and parameters that describe structure (e.g., d/n).

To implement the Bayesian procedure, parameters are drawn from a bootstrap likelihood as follows. First, compute non-linear, seemingly unrelated (NSUR) estimates of equations 11 and 4 using the original data sample. Let b denote the vector of parameter estimates computed from the original data sample, and let C denote the covariance matrix of b. Second, the residuals of the estimated nonlinear model are collected and adjusted for degrees of freedom.[6] Third, a bootstrap sample of adjusted residuals is drawn by selecting, with replacement, row vectors of the original, adjusted residuals. The ith bootstrap sample of data is constructed from the ith sample of bootstrap residuals, b, and the model. Fourth, an NSUR estimate of the model's parameter vector is computed for the ith bootstrap sample. Let b_i^* denote the parameter vector estimate associated with the ith bootstrap sample, and let C_i^* denote the covariance matrix of b_i^*. Fifth, the estimates computed in the previous steps are used to make the ith draw of the parameter vector, B_i, from the bootstrap likelihood as (Reed and Hallahan, 1994)

$$B_i = b - C^{1/2}(C_i^*)^{-1/2}(b_i^* - b).$$

A prior distribution is used to evaluate draws from the likelihood and is combined with the likelihood to form the posterior. The unrestricted prior is specified as a uniform distribution because the posterior is based, almost exclusively, on information in the data (Zellner, 1987). A restricted prior imposes transversality on a dynamic optimization problem, allowing it to be solved for an optimal solution sequence. Transversality conditions refer to ending conditions that ensure a bounded, infinite stream optimization. For this problem, the restricted prior is uniform over the region $d/n > 0$ and $|\rho_1| < 1$ and degenerate elsewhere.[7] While the restricted prior can be used to impose transversality, the unrestricted prior is used to evaluate the support for the restrictions in the data.

The restricted and unrestricted posteriors are used to measure the proportion of draws of (n+1)/n that fall in the interval [0.95, 1.05], (1.05, 1.95), and [1.95, 2.05]. The proportions are estimates of the probability that the data support the hypothesis of perfect competition, Cournot oligopoly, and perfect collusion, respectively. The proportion of draws outside the interval [0.95,2.05] represents the probability that the data support a more complicated, possibly non-recursive, oligopoly.

Results

Monthly data on farm prices, $\{w_t\}$, retail prices, $\{p_t\}$, and farm commodity production, $\{F_t\}$ for the U.S. beef, pork, and dairy industries from 1970 to 1993 are aggregated to quarterly data and used in the analysis. The data series used are described in the Appendix.

Point estimates of A_1 for the three industries are computed using retail food price data, the level of the farm commodity produced, an estimate of the output-input coefficient (ϕ) , and Huang's (1988) flexibility estimate. Multiplying Huang's flexibility estimate by the ratio of the sample average of retail price to the sample average of food consumption (i.e., $\{\phi F_t\}$) gives the point estimate of A_1. Huang's flexibility estimate and USDA's estimate of ϕ are reported in the Appendix, and the point estimates of A_1 are reported in table 1a.

Because the empirical analysis involves estimating the parameters of a dynamic model, the possibility of unit root nonstationarity cannot be ignored. Unit root nonstationary time series contain stochastic time trends that violate conditions needed to ensure consistency and valid statistical inference in classical regression (White 1984). Dickey and Fountis (1989) propose a method to test for a unit root in a vector time series. If the unit root cannot be rejected, the Dickey and Fountis method rotates a VAR representation of the time series so steady-state relationships can be estimated, and the stochastic trend can be removed. Once the stochastic trend is removed, the parameters of the dynamic model are estimated.

The Dickey-Fountis method is implemented by estimating a VAR of order one for farm price, farm commodity production, and retail price (see Dickey and Fountis). Dickey-Fuller test statistics computed for the multivariate models are -1.81, -4.14, and -1.36 for the beef, pork, and dairy industries, respectively. According to Table 8.5.1 of Fuller (p. 371), the hypothesis of a single unit root cannot be rejected at the $\alpha = .05$ level of confidence if the test statistic is less than -13.7. The computed statistics suggest that the presence of a single unit root in each of the three time series cannot be rejected with any reasonable level of confidence.

As described by Dickey and Fountis, each trivariate VAR is rotated using estimates of two cointegrating vectors. The two cointegrating vectors provide two linear, steady-state or longrun relationships among retail price, farm price, and farm quantity series. The economic model assigns the longrun relationship between farm price and farm output to the B_1 parameter of equation 3. The two cointegrating relationships are solved for this single relationship, and estimates of the B_1 parameter are reported in table 1a.

Each VAR is also rotated in a single, unit-root nonstationary direction. The vector used for this rotation is a linear combination that, when applied to a vector time series, forms a system variable used to remove the stochastic trend. Detrended farm quantity and retail price data, point estimates of A_1 and ϕ , and equation 2 are used to construct the detrended demand shift sequence, $\{u_t\}$. Detrended data are used to compute estimates of the economic model as described in the previous section. Tables 1a and 1b report the unrestricted means and the standard deviations of the posterior, and table 2 reports probability estimates of the intervals associated with the different types of conduct. The results are based on 1,100 draws from the bootstrap likelihood.[8] The probability estimates reported in table 2 indicate the transversality condition is almost always satisfied for the three sets of data, and, although not reported, the point estimates of the restricted posterior, in which transversality is imposed, are almost identical to the unrestricted estimates. Hence, only the unrestricted results are discussed in the remainder of this section.

The point estimates of (n+1)/n reported in table 1 are, on average, outside the interval [0.95,2.05] for each of the three industry data sets. Furthermore, table 2 reports a zero probability that (n+1)/n falls in the interval [0.95,2.05] in the beef and pork industries; and a 0.046 probability (n+1)/n falls in [0.95,2.05] in the dairy industry. The results imply that, with probability 1 in the beef and pork industries, and with probability 0.954 in the dairy industry, firm conduct is not perfectly competitive, nor perfectly collusive, nor a non-cooperative Cournot-Nash oligopoly.

Despite the suggestion that conduct does not fall into one of the three categories, the results reported in tables 1 and 2 indicate that differences in structure among the industries may be more influential in generating market-level data than are differences in firm conduct. Table 1a reports the estimates of A_1 and B_1, as well as the means and standard deviations of the posterior of the (d/n) and the ρ_1 parameters. The estimate of (d/n) is the smallest in the dairy industry (.013) and largest in the beef industry (.1076). The structural parameters reported in table 1a, however, are not strictly comparable across industries.

The estimates reported in the first three columns of table 1b are comparable across industries, and provide an interpretation of the movement of market data. As stated above, the magnitude of λ largely determines the fluctuation in market indicators. The results indicate that λ is, on average and among the three industries, largest in the beef industry, smallest in the dairy industry, and intermediate in the pork industry. The results suggest that, among firms in the three industries, and conditioned on differences in the distribution of demand shifts, firms in the beef industry make the largest adjustments to production, and generate the most fluctuation in market data. The results also suggest that, among the three industries, dairy firms take the smallest steps and generate the least fluctuation in market indicators. Finally, pork producers take an intermediate amount of time to make a full adjustment to a change in market conditions. The results suggest differences of λ between the beef and pork sectors are attributed more to differences in the d/n parameter than to differences in the nature of competition. The results suggest that if firms in the pork industry realize further economies of coordinating capital, d/n may continue to fall, and fluctuations in pork-market indicators will diminish further.

The question arises as to whether differences in fluctuation of market indicators among industries are due primarily to price-insensitive consumers or to price insensitive-farm producers. Recent studies by Thurman, and Kinsey suggest it is price insensitivity of consumers that will continue to drive changes in the performance of food markets. Other authors, such as Rogers and Sexton (1994), suggest a farm sector with more specialized resources induce oligopsony power among food producers and lead, perhaps, to a less price-responsive farm sector. The first two columns of table 1b attempt to measure the contribution of consumers and farm producers to the "step-size" of market indicators. Specifically, the magnitude of $\{A_1[(n+1)/n]\}/(d/n)$ measures the conduct-adjusted contribution of consumer preferences to market fluctuations, and the ratio $\{B_1[(n+1)/n]\}/(d/n)$ measures the conduct-adjusted contribution of farm-producers' technology to market fluctuations.

Estimates of the ratios reported in table 1b suggest consumer preferences and the nature of farm-level production contribute about equally to market fluctuations in the beef industry. In the pork and dairy industries, however, consumer preferences make a significantly larger contribution to market fluctuations than do farm producers. The results suggest that when firms in the pork and dairy industries respond to changing market forces, they weigh the expected fluctuation in revenues from the sale of food to consumers more than the expected fluctuation in farm-ingredient costs. The results reported in the first two columns of table 1b appear not to be explained by differences in firm conduct.

Table 1b reports the estimates of $\lambda/(d/n)$ for the three industries. Again, a relatively large value of $(\lambda/(d/n))$ indicates that the stream of consumer demand shifts is important in determining the decisions of food-producing firms. As stated above, theory indicates that the direction of change of $(\lambda/(d/n))$ is ambiguous in "new" markets with less price-sensitive consumers (i.e., A_1 increases) and increases in economies of scope (i.e., (d/n) declines). The results reported in Tables 1a and 1b indicate that, if industries are sorted by increasing magnitude of $\lambda/(d/n)$, they are also sorted by decreases in the d/n or A_1 or B_1. The results suggest that the industry's response to consumer shifts may become more important in "new" markets.

Theory indicates that, as firm conduct becomes more perfectly competitive, the response of the market to the stream of demand shifts should increase. Formally, as the parameter (n+1)/n decreases (to unity) the coefficient, $\lambda/(d/n)$, increases. This pattern is not borne out by the results reported in tables 1a and 1b. Sorting the industries by increasing average values of (n+1)/n results in a sorting by increasing values of $\lambda/(d/n)$. The results indicate that not only does competition not fall into a game associated with this class of models, but that, for one to understanding patterns in market data, the nature of competition appears to be less important than changes in consumer preferences and re-organization of food producers

Conclusions

This paper attempted to empirically identify firm conduct in selected food industries using market-level data and an optimization framework. The empirical results appear inconclusive, however, for two main reasons.

First, the economic model assumes that firm conduct remains fixed. Schroeter and Azzam's empirical estimates were interpretable only when estimates of the conduct parameter were permitted to change with time. Despite removing stochastic time trends from the data, and treating true conduct parameters as random variables rather than as fixed parameters, the results do not identify the nature of competition in the three food industries. Evidently, the problem lies in incorporating alternative, and perhaps more realistic conduct into the conceptual framework. By constructing reasonable punishment strategies, Koontz, Garcia, and Hudson (1993) provide conceptual reasons why firms switch conduct and why oligopoly/oligopsony does not lie on a continuum between perfect competition and monopoly/monopsony. Given that the estimates of the conduct parameter reported above lie outside this continuum, the idea that conduct remains fixed may need to be re-examined in light of the Koontz, Garcia, and Hudson work.

Second, market-level data may not be appropriate to identify conduct in an explicitly shortrun analysis. Structural differences among competitors, not accounted for in the above analysis, may distort inference on shortrun conduct. Indeed, anti-trust, or Capper-Volstead, investigations have typically focused on regional markets or on the conduct of individual firms. As Koontz, Garcia, and Hudson illustrate, the use of disaggregate data leads to new and interesting ways to think about conduct.

Table 1a -- Unrestricted estimates, consumers, processors, commodity suppliers*

Commodity	n+1/n	d/n	ρ_1	A_1	B_1
BEEF*	0.2644 (.033)	0.1076 (.040)	0.8960 (.091)	0.0687	0.0665
PORK	0.2872 (.049)	0.0524 (.008)	0.5649 (.073)	0.0650	0.0249
DAIRY	3.282 (1.4)	0.0130 (.003)	0.6019 (.105)	0.0017	0.0003

Table 1b -- Unrestricted estimates, market response*

Commodity	$\frac{[(n+1)/n]A_1}{d/n}$	$\frac{[(n+1)/n]B_1}{d/n}$	λ	$\frac{\lambda}{(d/n)}$
BEEF*	0.1875 (.063)	0.1812 (.061)	0.6280 (.048)	6.396 (1.7)
PORK	0.3622 (.068)	0.1390 (.026)	0.5672 (.031)	11.02 (1.3)
DAIRY	0.4077 (.058)	0.0883 (.012)	0.5112 (.022)	41.61 (9.7)

* Based on 1,093 draws from the bootstrap likelihood. Seven draws were discarded because of unstable results.

Table 2 -- Probabilities of interest

Item	Unrestricted	Transversality conditions imposed
BEEF		
P(Transversality)	0.880	1.0
P(Cournot)	0.000	0.000
P(Competition)	0.000	0.000
P(Collusion)	0.000	0.000
PORK		
P(Transversality)	1.0	1.0
P(Cournot)	0.000	0.000
P(Competition)	0.000	0.000
P(Collusion)	0.000	0.000
DAIRY		
P(Transversality)	0.9840	1.0
P(Cournot)	0.0182	0.00848
P(Competition)	0.000	0.000
P(Collusion)	0.0282	0.02865

[1]Without implication, the author thanks Steve Martinez for providing useful comments on topics related to this paper.

[2]The firm's information set in period t includes the values of the variables of the model realized both prior to, and including period t. Consumer demand shifts, u_t, and commodity supply shifts ϵ_{1t} are realized in the beginning of period t. Once f_t and F_t are determined, they are included in the information set associated with period t.

[3]Equations 2, 3, and 6 represent a well-defined equilibrium. Let equation 5 generate the sequence, $\{F_t^*\}$. Substituting equation 5 into the consumer demand equation (equation 2) and the commodity supply equation (equation 3) gives market-clearing consumer and commodity prices, $\{p_t^*, w_t^*\}$. The trivariate sequence, $\{F_t^*, p_t^*, w_t^*\}$, represents an equilibrium in the following sense: (a) given market-clearing food and farm price sequences, $\{p_t^*, w_t^*\}$, the representative firm's sequence, $\{f_t^*\} \equiv \{F_t^*/n\}$, maximizes equation 1; and (b) the commodity sequence, $\{F_t^*\}$, clears the food and farm market at the bivariate price sequence, $\{p_t^*, w_t^*\}$.

[4]z is a complex variable in frequency domain that replaces the lag operator in the time domain.

[5]Perhaps using a t-test and an arbitrarily chosen size of the rejection region.

[6]The residuals are multiplied by $[N/(N-k)]^{1/2}$ where N is the product of the number of equations times the number of observations, and k is the number of parameters in the system (McCullough and Vinod).

[7]Strictly speaking, this pair of conditions is sufficient for transversality if $(n+1)/n > 0$.

[8]Draws from the likelihood that resulted in an unstable regression were discarded. When the ratio of the smallest to the largest eigenvalues of the second moment of the gradient matrix for the nonlinear problem is less than $1x10^{-13}$, the draw was discarded. This occurred only seven times using the beef data.

References

Appelbaum, E. "Testing Price Taking Behavior." *J. of Econometrics* 9(February 1979):283-294.

Appelbaum, E. "The Estimation of the Degree of Oligopoly Power." *J. of Econometrics* 19(August 1982):287-299.

Commodity Futures Trading Commission. *An Analysis of Intraday Trading of Beef Packers in Live Cattle Futures.* Report prepared by the Market Surveillance Section Division of Economic Analysis. (September 1994).

Dickey, D.A., and N.G. Fountis. "Testing for a Unit Root Nonstationarity in Multi variate Autoregressive Time Series." *The Annals of Statistics* 17(March 1989):419-428.

Drabenstott, M. "Industrialization: Steady Current or Tidal Wave?" *Choices* (Fourth Quarter 1994):4-7.

Fuller, W.A. *Introduction to Statistical Time Series.* New York: John Wiley & Sons, 1976.

Gallant, A.R. *Nonlinear Statistical Models.* New York: John Wiley & Sons, 1987.

Hansen, L.P., D. Epple, and W. Roberds. "Linear-Quadratic Duopoly Models of Resource Depletion." *Energy, Foresight & Strategy,* T.J. Sargent, ed. Washington: Resources for the Future, 1985.

Henderson, D.R., S. McCorriston, and I. *Sheldon. Vertical Coordination: Concept, Practice, Theory and Policy. Implications for the Agro-Food Sector.* Organization and Performance of World Food Systems: NC-194. OP-50 (Sept. 1993).

Holloway, G.J. "The Farm-Retail Price Spread in an Imperfectly Competitive Food Industry." *Amer. J. Agr. Econ.* 73(November 1991):979-989.

Huang, K. "An Inverse Demand System for U.S. Composite Goods." *Amer. J. Agr. Econ.* 70(November 1988):902-909.

Hyde, C.E., and J.M. Perloff. "Can Monopsony Power be Estimated?" *Amer. J. Agr. Econ.* 76(December 1994):1151-1155.

Karp, L.S., and J.M. Perloff. "A Dynamic Model of Oligopoly in the Coffee Export Market." *Amer. J. Agr. Econ.* 75(May 1993):448-457.

Kinsey, J. "Changes in Food Consumption from Mass Market to Niche Markets." in *Food and Agricultural Markets: The Quiet Revolution*, L.P. Schertz and L.M. Daft, eds., Washington, D.C: Food and Agricultural Committee Nat'l Planning Association Report No. 270 (1994).

Koontz, S.R., P. Garcia, and M.A. Hudson. "Meatpacker Conduct in Fed Cattle Pricing: An Investigation of Oligopsony Power." *Amer. J. Agr. Econ.* 73(August 1993):537-548.

McCorriston, S., and I.M. Sheldon. "Economics of Vertical Restraints and its Relevance to Competition Policy in the Food Marketing System." Working Paper ESO-2241. Columbus: The Dept. of Agr. Economics, The Ohio State University. (July 1995).

McCullough, B.D., and H. Vinod. "Implementing the Single Bootstrap: Some Computational Considerations." *Computational Econ.* 6(February 1993):1-15.

Mighell, R.L., and L.A. Jones. "Vertical Coordination in Agriculture." AER-19. U.S. Dept. of Agr., Econ. Res. Serv. (February 1963).

Paul, Allen B. "The Role of Competitive Market Institutions." *The J. of Agr. Econ. Research.* 26(April 1974).

Reed, A.J., and C. Hallahan. "A Bootstrap Estimator for Dynamic Optimization Models." *Computational Techniques for Econometrics and Economic Analysis,* D.A. Belsley, ed., Dordrecht: Kluwer Academic Publishers, 1994.

Rogers, R.T., and R.J. Sexton. "Assessing the Importance of Oligopsony Power in Agricultural Markets." *Amer. J. Agr. Econ.* 76(December 1994):1143-1150.

Sargent, T.J. *Macroeconomic Theory.* Boston: Academic Press, 1987.

Schroeter and Azzam. "Marketing Margins, Market Power, and Price Uncertainty." *Amer. J. Agr. Econ.* 73(November 1991):990-999.

Thurman, W.N. "Have Meat Price and Income Elasticities Changed? Their Connection with Changes in Marketing Channels." In *The Economics of Meat Demand,* R.C. Buse, ed., Proceedings of a Conference on The Economics of Meat Demand, cosponsored by the Board of Agriculture of the National Research Council and the Sourthern Regional Research Project (S-165). Charleston, South Carolina (October 20-21, 1986).

Townsend, R.M. "Forecasting the Forecasts of Others." *J. of Polit. Econ.* 91(August 1983):546-587.

White, H. *Asymptotic Theory for Econometricians.* Orlando: Academic Press, 1984.

Wohlgenant, M.K., and R.C. Haidacher. "Retail to Farm Linkage for a Complete Demand System of Food Commodities." U.S. Dept. Agr., Econ Res. Serv., TB-1775. (December 1989).

Zellner, A. *An Introduction to Bayesian Inference in Econometrics.* Malabar: R.E. Krieger Publishing Company, 1987.

Appendix

This Appendix reports the titles of monthly data series on farm prices, farm production, and retail prices used in constructing the detrended quarterly data used in the analysis. All data were obtained from publicly available files of the Economic Research Service of the USDA, and span the period 1970.1 to 1993.7. The title of each sample series, its unit of measurement, and the symbol used in the model are reported below. The parameters fixed for each industry are reported in parentheses.

1. Beef (β=0.95, ϕ=0.600, *flex*=1.082)

- (w_t): Prices received by farmers, cattle, all beef ($/cwt):
- (F_t): Cattle production, federally inspected U.S. (million lbs)
- (p_t): Grade 3, choice beef (cents/retail lb)

2. Pork (β=0.95, ϕ=0.776, *flex*=1.222)

- (w_t): Prices received by farmers, all hogs ($/cwt) ($w_t$)
- (F_t): Pork production, federally inspected (million lbs)
- (p_t): Pork, US retail price (cents/retail lb)

3. Dairy (β=0.95, ϕ=1.000, *flex*=0.609)

- (w_t): Prices received by farmers, all milk ($/cwt)
- (F_t): Milk production, US, 50 states (million lbs)
- (p_t): CPI: dairy products (1982-84=100)