

GSIR WORKING PAPERS

Economic Development & Policy Series EDP06-4

Measuring Market Power in a Dynamic Oligopoly Model: The Dallas-Forth Worth Milk Market Case

Donghun KIM
International University of Japan

January 2006

Graduate School of International Relations
International University of Japan

<http://gsir.iuj.ac.jp/>



Measuring Market Power in a Dynamic Oligopoly Model: The Dallas-Forth Worth Milk Market Case

Donghun Kim*

Assistant Professor, International Development Program, Graduate School of
International Relations, International University of Japan

ABSTRACT

We derive a dynamic structural model based on a dynamic supergame model and measure market power for the Dallas-Forth Worth milk market in the U.S. In particular, we analyze the cyclical behavior of firm conduct and evaluate bias in static market-power measures in a unified manner by deriving and estimating a dynamic first-order condition for profit maximization. We find that firm conduct in the Dallas-Forth Worth milk market is countercyclical against demand shocks and expected future cost shocks. We also demonstrate that the conduct parameter in a static model underestimates true market power if firms' behaviors are posited by a dynamic supergame.

Keywords: Dallas-Fort Worth Milk Market, Conduct Parameter, Dynamic Supergame, Market Power, Collusion

JEL classification: D4, L0, Q0

GSIR working papers are preliminary research documents, published by the Graduate School of International Relations. To facilitate prompt distribution, they have not been formally reviewed and edited. They are circulated in order to stimulate discussion and critical comment and may be revised. The views and interpretations expressed in these papers are those of the author(s). It is expected that most working papers will be published in some other form.

* I thank Ronald W.Cotterill, Dirk Czarnitzki and participants at various conferences for helpful comments. The usual disclaimer applies.

Measuring Market Power in a Dynamic Oligopoly Model: The Dallas-Forth Worth Milk Market Case

Donghun Kim

Assistant Professor, International Development Program, Graduate School of
International Relations, International University of Japan

I. Introduction

Measuring the degree of competition in oligopolistic markets and finding the underlying determinants of such competition are key activities in empirical industrial organization. Earlier studies focused on estimating conduct parameters that distinguish collusive behaviors from non-collusive behaviors, using contemporary observations of outputs, costs, and prices. The literature on measuring oligopolistic conduct follows from original research by Iwata (1974), Gallop and Roberts (1979), and Appelbaum (1982).¹ The static contemporaneous conduct parameter is designed to estimate the level of market competition in a one-shot game that is repeated over time.²

As the problem of repeated oligopoly interaction has received greater attention, the estimation of time-varying conduct parameters that are truly dynamic has become an issue. Green and Porter (1984) predict a procyclical behavior pattern for markups because of price reversion during a period of low demand. Hence the conduct parameter changes from collusive value to competitive value when there is an unanticipated negative demand shock. Meanwhile, Rotemberg and Saloner (1986) predict that prices and markups are counter-cyclical. The incentive to deviate from collusive agreements is greater when demand is high, so the optimal price decreases during a boom to prevent a deviation from the collusion in this model. Hence the conduct parameter will decrease

¹ Other examples of studies estimating static conduct parameters include Brander and Zhang (1990), Graddy (1995), and Berg and Kim (1994)—analyzing the U.S. airline industry, the Fulton fish market in the U.S., and the Norwegian banking sector, respectively.

² Other methods for estimating market power are found in Hall (1988) and Panza-Ross (1987). See Hyde and Perloff (1995) for a comparison of various methods. Another approach in NEIO is to estimate the demand and pricing relationship under specific assumptions of market competition (Bresnahan, 1987). This approach has been used for differentiated product markets with price competition. See, for example, BLP (1995) and Nevo (2001).

when demand is high.

Empirical studies that estimate time-varying conduct include Bresnahan (1987), Brandar and Zhang (1993), and Gallet and Schroeter (1995). Bresnahan (1987) analyzes changes in firm conduct in the mid-1950s for the U.S automobile industry. He finds that, in the industry, the collusive solution is sustained in 1954 and in 1956 while the competitive solution holds in 1955. Brandar and Zhang (1993) estimate a regime-switching model that is derived from Green and Porter (1984) for the U.S. airline industry during the 1984-1988 period. They find that Bertrand, Cournot, or cartel one-shot static games are rejected and the reversion from collusion to Cournot behavior is strongly supported. Gallet and Schroeter (1995) estimate a countercyclical regime-switching model in favor of the Rotemberg-Woodford model for the 1930's U.S. rayon industry. Bresnahan (1987) estimates for a differentiated product market with price competition while Brandar and Zhang (1993), and Gallet and Schoreter (1995) estimate for homogeneous product markets with quantity setting.

Our goal in this paper is to analyze the cyclical behavior of firm conduct in the Dallas-Forth Worth milk market in the U.S. and evaluate bias in static market-power measures in a unified manner by deriving and estimating a dynamic first-order condition for profit maximization. To accomplish this, we specify a structural model that is based on a dynamic supergame model for firm-level conduct. In the model, firms sell differentiated products and choose prices so as to maximize their profits, comparing the benefit of a deviation from collusion with the expected future loss from the deviation. As in Rotemberg and Saloner (1986) and Green and Porter (1984), there are cyclical patterns of prices or markups in our model as firm conduct changes over time. We assume, however, that there remains a time-invariant conduct parameter that measures an average level of market power in the dynamic model. We call this a 'core conduct parameter.' We then model a dynamic conduct parameter as a function of the core conduct parameter, demand shocks, and cost shocks. The demand shocks and cost shocks cause the dynamic conduct parameter to deviate from the core conduct parameter. Hence we combine the concept of estimating an average level of collusiveness with that of estimating time-varying firm behavior in a single model. For example, if firms behave

as posited by Rotemberg and Saloner (1986), they will impose cartel prices when no incentive compatibility condition is binding and will charge prices lower than cartel prices when an incentive compatibility condition binds. Hence the conduct parameter will be higher when no incentive compatibility condition is binding than when such a condition is binding. But there still exists an average level of market power, which is consistently sustained if firms follow a dynamic tacit collusion game. We also specify an empirical model based on static profit maximization to compare the conduct parameter estimates from a static model with the core conduct parameter and to illustrate bias in the market-power measure in a static model. Corts (1995) suggests that the conduct parameter captures the marginal response of the margins to demand shocks and that it can misrepresent the level of market power if firm behavior in a market follows a dynamic oligopoly game. In this paper, we relate the bias in the measurement of the conduct parameter to costs and demand shocks which affect the incentive compatibility constraint, and show that the omission of the costs and demand shock in the specification of an econometric model can generate the bias.

Our data consists of supermarket-level prices, quantities, and cost data in the Dallas-Forth Worth area of the U.S. The data is monthly, for the period of March 1996 to July 2000. It contains five supermarkets that cover 73% of the total milk market in the area. Supermarkets compete with one another constantly and this may provide an incentive for tacit collusion. We construct a panel data set by combining the individual supermarket data.

We find that the empirical results for the Dallas-Forth Worth milk market are consistent with the prediction of a dynamic supergame that the conduct parameter will be greater than it would be under Nash-Bertrand competition and lower than cartel level if firm conduct follows a dynamic oligopoly game. The current demand shock relative to expected future demand has a significant and negative effect on firm conduct. The dynamic conduct parameter is, therefore, less than the core conduct parameter during the boom. And expected future cost shock has a countercyclical effect on firm conduct.

Empirical results also demonstrate that the static conduct parameter underestimates the degree of collusion in the Dallas-Forth Worth milk market.

Econometrically, the static model is a restricted version of the full model that is derived from dynamic profit maximization. Tests reject the restriction. The static model underestimates the average conduct parameter of the dynamic model by more than 33% and its price-cost margins by 9%. This indicates that specifying and estimating static oligopoly models can misrepresent the degree of market power. We also specify different forms of marginal cost function to test the sensitivity of the result. The results of these tests show that the conduct parameter under a linear specification is slightly smaller than it is under a semi-log specification, but that it is a bit greater than it is under a quadratic specification. Meanwhile, in each specification, the conduct parameter of the static model has a tendency to underestimate the conduct parameter of the dynamic specification.

The paper is organized as follows. First, in Part II, we describe the Dallas-Forth Worth milk market and the corresponding data. In Part III, we specify a dynamic supergame model. We analyze empirical results in Part IV and present concluding comments in Part V.

II. Market and Data

The scanner data used in this analysis was obtained from Information Resources Inc (IRI). IRI collects retail grocery product sales and merchadising data from a national sample of 12,080 supermarkets with annual sales greater than 2 million dollars. The data is a census-enhanced database constructed from 100% of the representative key accounts stores and a sample technique to estimate the remaining stores in each region that do not report full sales data. Data is then grouped by market area defined by local county definitions.

Our data consists of supermarket-level prices, quantities, and cost data in the Dallas-Forth Worth area of the U.S. The market population is 4.7 million, with 1.7 million households. The median household income is 44 thousand dollars. The median age is 33 and household size is 2.7 persons. The data come from five supermarkets that cover 73% of the total milk market in the area. The supermarkets include Albertsons, Kroger, Minyard, Win Dixie and Tom Thumb. The data is monthly, for the period of

March 1996 to July 2000. Table 1 shows the sample statistics. p_i is own price and p_j is other firm's price, which is a volume-weighted sum of the other firms' prices. *Income* is median income level in the market. *RawMilk_t*, *Electricity_t*, *Wage_t*, and *PackingCost_t* are monthly price indexes for raw milk, electricity, wages, and packing cost. *InterestRate_t* is included to capture the effect of capital cost. The proxy for capital cost is the monthly prime interest rate.

III. Specification of A Dynamic Supergame Model

We assume that milk products are differentiated across supermarket chains. Supermarkets charge different prices and exhibit different merchandising activity for milk. Firm i 's profit function in a differentiated product market is:

$$\pi_i = p_i q_i(p_i, p_j) - C(q_i(p_i, p_j)) \quad (1)$$

Where π_i is a firm i 's profit, p_i is a firm i 's price, and p_j is a price for firm j . $C(q_i(p_i, p_j))$ is a firm i 's cost function. We assume that a firm's marginal cost is constant but that it varies across firms and over time. Finally, we represent a firm i 's demand function, q_i , as follows:

$$q_i = \alpha_0 + \alpha_1 \cdot p_i + \alpha_2 \cdot p_j + f(\text{Demand Shifters}) + \varepsilon_i \quad (2)$$

Here ε_i is an error term and α_i 's are parameters to be estimated.

We define a trigger strategy for a supergame such that each firm begins by charging cartel prices and continues to do so as long as all other players do the same. Otherwise firms revert to Nash-Bertrand prices following any defection and continue to play the Nash-Bertrand game forever.³ We assume that a firm observes prices for $t=1, 2, \dots, t-1$ at time T . Each firm solves a dynamic profit maximization problem by comparing the benefit of a deviation from the collusion with the future loss caused by retaliation.⁴ We can then write a firm's profit maximization condition as follows:

³ See Friedman (1971). This is his 'grim trigger' strategy.

⁴ See Rothschild (1992) for the sustainability of collusion in differentiated duopolies when price is the strategic variable and Rothschild (1995) for the sustainability of collusion in differentiated product

$$\begin{aligned}
p^*(x_t, w_t, \delta) &= \arg \max \pi(p; x_t, w_t) \\
s.t. \quad \pi^b(p; x_t, w_t) &+ \sum_{i=1}^{\infty} \delta^i E_t[\pi^{nb}(x_{t+i}, w_{t+i})] \leq \pi(p; x_t, w_t) \\
&+ \sum_{i=1}^{\infty} \delta^i E_t[\pi(p^*(x_{t+i}, w_{t+i}, \delta); x_{t+i}, w_{t+i})]
\end{aligned} \tag{3}$$

Here $\pi^b(p; x_t, w_t)$ is a firm's best response profit at time t . x_t and w_t are a demand shock and a cost shock at time t , respectively. $\pi^{nb}(p; x_t, w_t)$ is the profit for the retaliation period. If all other firms play their Nash-Bertrand equilibrium strategy in every period, the best that a single firm can do is to play its Nash-Bertrand equilibrium strategy in each period. We assume that firms revert to Nash-Bertrand competition during that period. $\pi(p^*; x_{t+i}, w_{t+i})$ is a firm's profit that is obtained when collusion is sustained and p^* is the optimal collusive price. δ is a discount rate. Then the future expected loss from the deviation is:

$\sum_{i=1}^{\infty} \delta^i E_t[\pi(p^*(x_{t+i}, w_{t+i}, \delta); x_{t+i}, w_{t+i}) - \pi^{nb}(x_{t+i}, w_{t+i})]$. Following this, the first-order condition for profit maximization is:

$$(1 + \psi) \{ q_{it} + [p_{it} - mc_{it}] \cdot \left(\frac{\partial q_{it}}{\partial p_{it}} + \frac{\partial q_{it}}{\partial p_{jt}} \cdot \frac{\partial p_{jt}}{\partial p_{it}} \right) \} - \psi \cdot \frac{\partial \pi^b(p; x_t, w_t)}{\partial p_{it}} = 0 \tag{4}$$

Where ψ is a Lagrange multiplier. The dynamic first-order condition can be written as:

$$q_{it} + [p_{it} - mc_{it}] \cdot \left(\frac{\partial q_{it}}{\partial p_{it}} + \frac{\partial q_{it}}{\partial p_{jt}} \cdot \theta^* \right) - \frac{\psi}{1 + \psi} \cdot \frac{\partial \pi^b(p; x_t, w_t)}{\partial p_{it}} = 0 \tag{5}$$

In (5) the conduct will change depending on whether the incentive compatibility condition binds. But there is an average level of this time-varying conduct parameter,

markets when strategic variables can be switched. Deneckere (1983) shows that when products are good substitutes, collusion is better supported in price-setting games.

θ^* , and we call it the core conduct parameter. Theoretically, $\theta^* = \frac{\partial p_{jt}}{\partial p_{it}}$, $\frac{\partial q_{it}}{\partial p_{it}} = \alpha_1$ and

$\frac{\partial q_{it}}{\partial p_{jt}} = \alpha_2$. If $\theta^* = 0$, then a firm's conduct is consistent with Nash-Bertrand

competition. If $0 < \theta^* < 1$, a firm's behavior is partially collusive, and if $\theta^* = 1$, it is fully collusive. Only when the constraint does not bind, i.e. when $\psi = 0$, is it the same as the static conduct parameter that solves the static first-order condition:

$$q_{it} + [p_{it} - mc_{it}] \cdot \left(\frac{\partial q_{it}}{\partial p_{it}} + \frac{\partial q_{it}}{\partial p_{jt}} \cdot \theta \right) = 0 \quad (6)$$

If the static model is correct, the error term in an econometric model for (6) is a pure stochastic term and therefore should not affect a firm's pricing behavior. If other dynamic factors influence the prices, omitted variable bias in estimating a static model and the static conduct parameter is possible. This implies that the static conduct parameter θ can under- or overestimate the core conduct parameter, depending on the sign of $\frac{\partial \pi^b(p; x_t, w_t)}{\partial p_{it}}$ when ψ is greater than zero.

We now specify a dynamic conduct parameter, θ_t , to analyze the cyclical behavior of firm conduct. We can model the dynamic conduct parameter as a function of the core conduct parameter and a term that is a function of $\frac{\psi}{1+\psi} \cdot \frac{\partial \pi^b(p; x_t, w_t)}{\partial p_{it}}$ in the pricing relationship (5).

$$\theta_t = \theta^* + \gamma \left[\frac{\psi}{1+\psi} \cdot \frac{\partial \pi^b(p; x_t, w_t)}{\partial p_{it}} \right] \quad (7)$$

In the specification in (7), the first term, the core conduct parameter, measures the average level of collusion over time while the second nonlinear term captures the deviation from the average level. We model $\frac{\psi}{1+\psi} \cdot \frac{\partial \pi^b(p; x_t, w_t)}{\partial p_{it}}$ as a function of

demand shocks and cost shocks because constraint binding and $\frac{\partial \pi^b(p; x_t, w_t)}{\partial p_{it}}$ are affected by them. We thus represent the dynamic conduct parameter as follows:

$$\theta_t = \theta^* + G(x_t, w_t) \quad (8)$$

Dynamic models predict that a firm's dynamic behavior is influenced by contemporary demand levels, expected future demand, and expected future costs. See, for example, Borenstein and Shephard (1996). We therefore specify $G(x_t, w_t)$ as a function of these variables:

$$\theta_t = \theta^* + \varphi_1 \cdot x_t + \varphi_2 \cdot w_t + e_t \quad (9)$$

Again, x_t and w_t represent demand shocks and cost shocks.

The advantages of the specification in (9) are two-fold. First, we can test the relationship between the firm's conduct and both demand shocks and cost shocks by specifying a time-varying conduct parameter.⁵ If x_t has a negative sign, this implies countercyclical firm conduct and markup as in Rotemberg and Saloner (1986). If x_t is positively associated with θ_t , this implies procyclical firm conduct and markups as in Green and Porter (1984).

Second, we can shed light on the source of bias that distinguishes the core conduct parameter θ^* in (5) and the static conduct parameter θ in (6). Suppose that the true game is a dynamic supergame and that the conduct parameter is a constant. Then we must estimate θ^* in (5). But if we assume a static game wrongly, we are then going to estimate θ in (6). This will produce a bias in the estimation of market power. What θ measures is not θ^* but θ^* plus a bias term. The bias term is a function of demand shock and cost shocks. In this case, market power will be underestimated or overestimated. Hence specification (9) is a way of estimating θ^* with a bias correction.

Thus the structural model to be estimated is:

⁵ See Bresnahan (1987), Brandar and Zhang (1993), and Gallet and Schroeter (1995) for time-varying conduct.

$$q_{it} = \alpha_0 + \alpha_1 \cdot p_{it} + \alpha_2 \cdot p_{jt} + \sum_{k=1}^{11} \alpha_{k+2} \cdot Mon_k + \sum_{i=1}^4 \alpha_{i+13} \cdot Sup_i + \alpha_{18} \cdot Income + \varepsilon_{it} \quad (10)$$

$$p_{it} = mc_{it} + \left[\frac{\partial q_{it}}{\partial p_{it}} + \frac{\partial q_{it}}{\partial p_{jt}} \cdot \theta_t \right]^{-1} q_{it} + v_{it} \quad (11)$$

$$\theta_t = \theta^* + \varphi_1 \cdot x_t + \varphi_2 \cdot w_t + e_t \quad (12)$$

$$mc_{it} = \gamma_0 + \gamma_1 \cdot InterestRate + \gamma_2 \cdot RawMilk_t + \gamma_3 \cdot Electricity_t + \gamma_5 \cdot Wage_t + \gamma_6 \cdot PackingCost_t + \sum_{i=1}^4 \gamma_{6+i} \cdot Sup_i + \delta_{it} \quad (13)$$

Firm i 's demand, q_i , is a function of own price, p_i , the other firm's price, p_j , a volume-weighted sum of the other firms' prices, Mon_k , a monthly dummy to control for seasonality, Sup_i , firm-specific dummies, and $Income$, the median income level in the market.⁶ Equation (11) represents firm i 's pricing relationship and the specification in (12) is the dynamic conduct parameter embedded in Equation (11). The dynamic conduct parameter is a function of θ^* , the core conduct parameter, x_t , demand shock, and w_t , cost shocks. To serve as a demand shock, x_t , we include current industry output divided by expected future output. As a proxy for future output, industry output at $t+1$ is used. For the cost shock, w_t , we use expected future cost rather than contemporary cost. The future cost shock is approximated by the raw milk price at $t+1$. If only static profit maximization matters, the parameters φ_1 and φ_2 should be equal to zero. Hence the static model is a restricted version of the full model (11). Therefore we can test to determine whether these restrictions are valid. We specify x_t and w_t in a mean deviation form so that the average of θ_t converges to θ^* . We specify a firm's marginal cost (13) as a function of the following factor prices and firm-specific dummies: $RawMilk_t$, $Electricity_t$, $Wage_t$, and $PackingCost_t$ are monthly price

⁶ Among variables, income is yearly and others are monthly.

indexes for raw milk, electricity, wages, and packing cost. $InterestRate_t$ is included to capture the effect of capital cost. The proxy for capital cost is the monthly prime interest rate. These input prices are market level. To capture the firm-level cost, we include fixed-effects dummies for each supermarket, SUP_i . The brand dummies represent the firm-specific production cost, which exhibits little variation over time (Nevo, 2001). ε_{it} , ν_{it} , e_t , and δ_{it} are error terms. We also specify different functional forms of marginal cost to test the sensitivity of the estimation of the conduct parameter. One is a semi-log linear form and the other is a quadratic form. Equation (14) represents the semi-log linear specification.

$$\begin{aligned}
mc_{it} = & \kappa_{0i} + \kappa_1 \cdot \ln(InterestRate_t) + \kappa_2 \cdot \ln(RawMilk_t) + \kappa_3 \cdot \ln(Electricity_t) \\
& + \kappa_4 \ln(pack_t) + \kappa_5 \cdot \ln(Wage_t) + \kappa_6 \cdot \ln(Packing Cost_t) + \delta_{it}
\end{aligned}
\tag{14}$$

In Equation (14), the input prices are specified in log form. k_{0i} represents firm fixed effects and k_i 's are parameters on the input prices. δ_{it} is an error term.

$$\begin{aligned}
mc_{it} = & \varpi_{0i} + \varpi_1 \cdot InterestRate_t + \varpi_2 \cdot (InterestRate_t)^2 + \varpi_3 \cdot RawMilk_t + \varpi_4 (Rawmilk_t)^2 \\
& + \varpi_5 \cdot Electricity_t + \varpi_6 (Electricity_t)^2 + \varpi_7 \cdot PackingCost_t + \varpi_8 \cdot (PackingCost_t)^2 \\
& + \varpi_9 \cdot Wage_t + \varpi_{10} (Wage_t)^2 + \varsigma_{it}
\end{aligned}
\tag{15}$$

Meanwhile, in Equation (15), ϖ_{0i} represents firm fixed effects and ϖ_i 's are parameters on the input prices. ς_{it} is an error term.

IV. Results

We estimate the structural model using the Generalized Method of Moments. We first estimate the demand side parameters and, given the estimated demand surface, we then estimate the pricing relationship. We estimate the demand and pricing relationships separately primarily to compare the core conductor parameter with the static conduct parameter given the estimated demand function. An example of two-step estimation of a

structural model is found in Nevo (2001). Table 2 shows the estimated demand-side parameters. We use cost variables such as raw milk price, packing cost, wages, and interest rates as well as exogenous variables in the demand equation as instrumental variables to control for price endogeneity. The value of the GMM objective function indicates that we are unable to reject the model specification at 10%, 5%, and 1%, respectively. Critical values for $\chi^2(4)$ are 7.78, 9.49, and 13.28 for each significance level. The coefficients on prices are significant and have the expected signs. The size of the coefficient on own price is greater than that on other firms' prices. This verifies that products are substitutes and strategic complements. The coefficient on own price implies that own-price elasticity is 1.509 and cross-price elasticity is 0.349. The elasticities are calculated at the mean in price and quantity. This implies that firm margin is around 66% under the assumption of Nash-Bertrand competition, because margin is simply the inverse of own-price elasticity. Price-cost margin can be defined as $[p - mc]/p = [\eta_{ii} - \theta \frac{p_i}{p_j} \cdot \eta_{ij}]^{-1}$ where η_{ii} is own-price elasticity and η_{ij} is cross-price elasticity. θ represents the conduct parameter. Under Nash-Bertrand competition, price-cost margin is equal to zero. Hence price-cost margin is simply the inverse of own-price elasticity.

Table 3 presents the estimation results for the fully dynamic pricing relationship. The instrumental variables for this estimation include monthly dummies, income, lagged quantity and the other firm's price, and exogenous variables. We are unable to reject the full model at the 5% significance level using the χ^2 test. The critical value for $\chi^2(13)$ is 22.36. In Table 3, raw milk price and wage are positive and significant among factor prices. On the other hand, packing cost has an unexpected sign but it is insignificant. The coefficient on interest is positive and insignificant. Roller and Sickles (2000) demonstrate that dropping capital cost resulted in bias in conduct parameter estimation for the European airline industry. The milk market might not, however, be as capital intensive as the airline industry, as the insignificant statistical result indicates. Meanwhile, the coefficients on the firm fixed effects, which capture the time-invariant

firm-specific marginal costs, are positive and significant.

The estimated core conduct parameter indicates that its size is 0.854 and it is significant at 1%. Hence the average level of market power is greater than the level of Nash-Bertrand competition and lower than the level of the cartel solution. This average level of market power also is greater than what is captured in the static model. In the static model the conduct parameter is estimated as 0.567 in Table 4. Hence the static model underestimates the average conduct parameter of the dynamic model by more than 33% and its price-cost margin by 9%.⁷ This implies that there can be a significant bias in measuring market power in a static model if actual firm behavior does not follow a one-shot static game.

The demand shocks and cost shocks have negative and significant effects on firm conduct. They are significant at the 5% level. The null hypothesis, that the parameters are equal to zero jointly, is also rejected. The test statistic, $\chi^2(2)$, is 15.34 and its critical value is 9.21 at the 1% significance level. We can test the validity of the restriction using the values of the GMM objective function of the full model and the restricted static model. $\chi^2(15) - \chi^2(13) = 28.71 - 13.37 = 15.34$. This test is attributed to Newey and West (1987).⁸ This demonstrates that the dynamic game matters in the Dallas-Forth Worth milk market. This result also indicates that the dynamic conduct parameter, θ_t , is countercyclical to current demand shock and expected future cost increase. Hence market prices are lower than cartel prices when current demand is higher than expected future demand and when firms expect future cost to increase. If expected future cost increases, then the expected loss from the deviation will decrease. This provides firms with an incentive to deviate from full collusion. The collusive market price must be lowered to prevent the deviation. The role of future cost is similar to that of current demand shock relative to future demand. The results also demonstrate that the static conduct parameter can underestimate market power when current demand relative to future demand increases and firms expect future cost to increase.

⁷ See Table 5.

⁸ Refer also to Greene (2003, p 549).

Table 6 compares the conduct parameters estimated under different specifications of marginal cost function. The results show that the conduct parameter under the linear specification is slightly smaller than it is under the semi-log specification, while it is a bit greater here than it is under the quadratic specification. Meanwhile, in each specification, the conduct parameter of the static model has a tendency to underestimate the conduct parameter of the dynamic specification.

V. Conclusion

In this paper we derive a structural model based on a dynamic oligopoly game and estimate market power for the Dallas-Forth Worth milk market in the U.S. In particular, we analyze the cyclical behavior of firm conduct and evaluate bias in static market-power measures in a unified manner by deriving and estimating a dynamic first-order condition for profit maximization. For these purposes, we collect supermarket-level prices, quantities, and cost data for the sample period of March 1996 to February 1999. Supermarkets compete with one another constantly and this may provide an incentive for tacit collusion.

The empirical results indicate that we are unable to reject the demand and pricing relationship specification. The coefficients of the demand function verify that milk products are substitutes and strategic complements. The estimated own-price elasticity is about 1.5. This suggests that firms' margin is around 66% under the assumption of Nash-Bertrand competition. We also find that the results for the Dallas-Forth Worth milk market are consistent with what dynamic oligopoly models predict. The estimated conduct parameter is greater than the Nash-Bertrand level and less than the cartel solution. And demand shock and future cost shock have countercyclical effects on current firm conduct. We also illuminate the source of bias in measuring market power using a static model. The static model is a restricted version of the full model that is derived from dynamic profit maximization. Tests reject the restriction. The static model underestimates the average conduct parameter of the dynamic model by more than 33% and its price-cost margins by 9%. This result demonstrates that fitting data into an

econometric model in an arbitrary manner can cause a misinterpretation of market power. We also find that the conduct parameter under a linear specification is slightly smaller than it is under a semi-log specification, but that it is a bit greater than it is under a quadratic specification. Meanwhile, in each specification, the conduct parameter of the static model has a tendency to underestimate the conduct parameter of the dynamic specification.

References

- Appelbaum, E., (1982), "The Estimation of the Degree of Oligopoly Power," *Journal of Econometrics*, 19, 287-299.
- Borenstein, Severin and Andrea Shepard, (1996), "Dynamic Pricing in Retail Gasoline Markets," *Rand Journal of Economics*, Vol 27, Issue 3, 429-451.
- Branda, A. James and Anming Zhang, (1993), "Dynamic Oligopoly Behavior in the Airline Industry", *International Journal of Industrial Organization*," Vol. 11, 407-435.
- Bresnahan, F. Timothy, (1987), "Competition and Collusion in the American Automobile Industry: The 1955 Price War," *Journal of Industrial Economics*, June, 457-482.
- Corts, Kenneth, (1999), "Conduct Parameters and the Measurement of Market Power," *Journal of Econometrics*, 88, 227-250.
- Deneckere, R., (1983), "Duopoly Supergame with Product Differentiation," *Economics Letters*, 11, 37-42.
- Ellison, Glenn, (1994), "Theories of Cartel Stability and the Joint Executive Committee," *Rand Journal of Economics*, 25(1), 37-57.
- Gallet, A. Graing and John R. Schroeter, (1995), "The Effects of the Business Cycle on Oligopoly Coordination: Evidence from the U.S. Rayon Industry", *Review of Industrial Organization*, 181-196.
- Gallop, D., and Roberts, M., (1979), "Firm Interdependence in Oligopolistic Markets," *Journal of Econometrics*, 10, 313-331.
- Green, Edward J., and Porter, Robert H, (1984), "Noncooperative Collusion Under Imperfect Price Information," *Econometrica*, 52(1), 87-100.
- Greene, H. William, (2003), *Econometric Analysis*, Fifth Edition, Prentice Hall.
- Genesove, David and Mullin, Wallace, (1998), "Testing Static Oligopoly Models: Conduct and Cost in the Sugar Industry, 1990-1914," *Rand Journal of Economics*, 29(2), 355-77.

- Hall, Robert E., (1988), "The Relationship Between Price and Marginal Cost in U.S industry", *Journal of Political Economy*, 96(5), 921-47.
- Hyde, Charles E. and Perloff, Jeffrey M., (1995), "Can Market Power Be Estimated?" *Review of Industrial Organization*, 10:465-485.
- Iwata, G., (1974), "Measurement of Conjectural Variations in Oligopoly," *Econometrica* 42, 949-966.
- MacDonald, James M., (2000), "Demand Information And Competition: Why Do Food Prices Fall at Seasonal Demand Peaks?" *Journal of Industrial Economics*, March, Vol XLVIII.
- Nevo, Aviv, 2001, "Measuring Market Power in the Ready-To-Eat Cereal Industry," *Econometrica*, 69, 307-402.
- Newey, W., and K. West, (1987), "Hypothesis Testing with Efficient Method of Moments Estimation," *International Economic Review*, 28, pp 777-787.
- Panza, John C., and Rosse, James N, (1987), "Testing for 'Monopoly' Equilibrium," *Journal of Industrial Economics*, 35(4), 443-56.
- Roller, Lars-Hendrik and Sickles, Robin C., (2000), "Capacity and Product Market Competition: Measuring Market Power In a 'Puppy-Dog' Industry," *International Journal of Industrial Organization*, 18, 845-865.
- Rotemberg, Julio J., and Saloner, Garth, (1986), "A Supergame-Theoretic Model of Price Wars During Booms," *American Economic Review*, 76(3), 390-407.
- Rothschild, R., (1992), "On the Sustainability of Collusion in Differentiated Duopolies," *Economics Letters*, 40, 33-37.
- Rothschild, R., (1995), "Sustaining Collusion When the Choice of Strategic Variable Is Endogenous," *Journal of Economics Behavior and Organization*, 28, 373-385.

Table 1) Sample statistics

Variable	Mean	Std Dev	Min	Max
p_i (\$/gallon)	3.055	0.293	2.465	3.870
p_j (\$/gallon)	3.051	0.249	2.599	3.703
q_i (million gallon)	0.648	0.213	0.318	1.063
$InterestRate_t$ (%)	8.308	0.234	7.750	8.500
$RawMilk_t$ (\$/gallon)	1.449	0.143	1.215	1.787
$Electricity_t$ (\$/hour)	4.015	0.116	3.700	4.200
$Wage_t$ (\$/hour)	11.755	0.339	10.980	12.300
$PackingCost_t$ (price index/100)	1.165	0.032	1.132	1.184
Median Income (ten thousand \$)	4.168	0.127	3.996	4.459

Table 2) Demand Side parameters

Variables	Parameter	Standard error
P_i	-0.351	0.041*
P_j	0.082	0.032**
Mon_1	-0.025	0.013***
Mon_2	0.002	0.014
Mon_3	-0.022	0.011**
Mon_4	-0.032	0.011*
Mon_5	-0.038	0.014*
Mon_6	-0.027	0.012**
Mon_7	-0.023	0.011**
Mon_8	0.005	0.013
Mon_9	-0.005	0.013
Mon_{10}	-0.009	0.012
Mon_{11}	-0.015	0.010
Sup_1	0.701	0.088*
Sup_2	0.409	0.085*
Sup_3	0.256	0.088*
Sup_4	0.064	0.087
Sup_5	0.389	0.110*
Median Income	0.058	0.022*
GMM Objective: $\chi^2(4)$	0.407	-

Note) *: Significant at 1%; **: Significant at 5%; ***: Significant at 10%.

Table 3) Parameters in the pricing relationship (full Model)

Variables	Parameter	Standard error
Marginal Cost		
<i>InterestRate</i>	0.153	0.169
<i>RawMilk</i>	0.979	0.291*
<i>Wage</i>	0.123	0.067***
<i>Electricity</i>	0.192	0.188
<i>PackingCost</i>	-0.107	0.252
<i>Sup₁</i>	3.869	2.317***
<i>Sup₂</i>	6.028	2.449**
<i>Sup₃</i>	7.512	2.570*
<i>Sup₄</i>	8.887	2.721*
<i>Sup₅</i>	7.661	2.551*
Conduct Parameter (θ_t)		
θ^*	0.854	0.117*
x_t	-0.691	0.313**
w_t	-0.271	0.119**
GMM objective: $\chi^2(13)$	13.368	-

Note) *: Significant at 1%; **: Significant at 5%; ***: Significant at 10%

Table 4) Parameters in the pricing relationship (Static Model)

Variables	Parameter	Standard error
Marginal Cost		
<i>InterestRate</i>	0.329	0.267
<i>RawMilk</i>	1.187	0.387*
<i>Wage</i>	0.139	0.057**
<i>Electricity</i>	0.295	0.241
<i>PackingCost</i>	-0.112	0.170
<i>Sup₁</i>	2.375	1.967
<i>Sup₂</i>	4.085	1.962**
<i>Sup₃</i>	5.241	1.978*
<i>Sup₄</i>	6.289	2.014*
<i>Sup₅</i>	5.413	1.972*
Conduct Parameter		
θ	0.567	0.081*
GMM objective: $\chi^2(15)$	28.712	-

Note) *: Significant at 1%; **: Significant at 5%; ***: Significant at 10%

Table 5) Firm conduct and implied margins

Conduct	Conduct parameter	Margins
Static conduct Model	0.567	76%
Dynamic conduct Model	0.854	83%

Table 6) Marginal Cost Functions and Conduct Parameter

The shape of marginal cost function	Dynamic Model	Static Model
Liner	0.812	0.604
Semi log linear	0.861	0.623
Quadratic function	0.684	0.442