Issues and Cautions in Employing Behavioral Modeling Approaches to Test for Market Power

Rodney Jones, Wayne Purcell, Paul Driscoll, and Everett Peterson[*]

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[*]Rodney Jones is a former USDA Marketing Needs Fellow; Wayne Purcell is Professor; and Paul Driscoll and Everett Peterson are Associate Professors in the Agricultural and Applied Economics Department at Virginia Tech.

INTRODUCTION

Recent increases in aggregate concentration have stimulated interest in measuring the degree of oligopoly or oligopsony market power.[1] Broad measures of aggregate concentration, especially in the industrial sectors, have shown increasing trends throughout this century (Sherer and Ross). Many individual U. S. industries are highly concentrated, dominated by a few large firms or corporations. In agricultural enterprises such as fruit and vegetable production, specialty grain production, and fed livestock production, many small farmers or livestock producers typically face a highly concentrated processing sector when, as producers, they sell their products. The actions of large firms in these industries may affect industry output, input procurement, and the pricing strategies pursued by rival firms in either output markets or input procurement markets.

If firms in these highly concentrated industries have the potential to exercise market power, then there is reason for public concern. Standard welfare economic theory demonstrates that any deviation of price from the competitive level will result in a net societal welfare loss. Available estimates of these welfare losses have been sensitive to model specification and data sources (Peterson and Connor). However, most studies have found that welfare losses do exist and that they could be quite significant. In addition, when market power is exercised, excess profits are reaped, leading to a redistribution of wealth from consumers and/or input suppliers to industry participants.

This bulletin focuses on the U. S. beef packing/processing industry, which has an interesting history of changing concentration levels and has played a major role in the evolution of U. S. antitrust policy.[2] Since the late 1970's, concentration levels in the beef packing industry have increased to where over 80 percent of the boxed beef trade in the U.S. is controlled by the four largest firms. Concentration measures in regional fed cattle procurement markets appear to be even higher (Ward, 1992).

Increases in firm concentration in the beef packing industry have been primarily the result of a series of horizontal mergers. The Federal Trade Commission (FTC) and/or the Department of Justice (DOJ) approved these mergers by relying heavily on arguments that society benefits from the economies of large size. There is some question as to whether the regulatory authorities fully considered the potential negative long-run implications of increased consolidation when making these decisions (Purcell, 1990).[3] In any event, increased concentration in beef packing has raised concerns regarding non-competitive pricing, particularly on the input or procurement side. Additional concerns have been voiced regarding the future of independent cattle producers when access to markets is reduced or restricted. Recent public pressure has prompted Congressional investigations regarding the potential exercise of market power by beef packers (United States General Accounting Office).

Previous researchers such as Quail *et al.* and Marion *et al.* have argued that the high levels of buyer concentration, particularly at the regional level, have resulted in decreased fed cattle prices. Others, such as Schroeter (1990), Azzam and Pagoulatos, and Koontz *et al.*, have argued that market power cannot be inferred from concentration levels alone. They contend that it is the behavior of the market participants that must be investigated if one is to identify the presence of market power.

Analysis of firm-level behavior requires detailed firm-level data on prices, quantities, and specific components of cost. Unfortunately, publicly available data are usually industry aggregates and the data observations often encompass long time intervals, such as calendar quarters or years. The implications of using such aggregated data to test for the existence of market power at the firm level have not been investigated, and potentially important policy issues remain unresolved.

Purpose Of Study

The purpose of this study is to investigate the sensitivity of empirical estimates of oligopsony power to

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[1]Oligopoly power is the ability to sell output at above the competitive price, and oligopsony power is the ability to procure inputs below the competitive price.

[2]The book by Yeager (see references) provides a thorough, detailed discussion of the history of the beef packing industry and it's important role in early U. S. antitrust policy.

[3]Potential long run problems arising in highly concentrated industries such as decreased new product development are also discussed in Geroski *et al.*

data aggregation and to model specification. Many previous market power studies have used data that were aggregated over various dimensions such as across firms, over time, or across input/output levels. The lack of firm-level data consistent with the decision time frame of the decision makers in the industry has forced such data choices. In order for aggregate industry data to be an adequate alternative to the desired firm-level data, several restrictive assumptions regarding the technology being used and the behavior of firms in the industry must hold. Specifically, all firms must have constant and equal marginal costs and must have the same beliefs about rival responses to their output changes. Previous research has indicated that marginal costs are not necessarily constant across firms in the beef packing industry (Ward, 1988 and Duewer and Nelson). Therefore, it is doubtful that the necessary restrictions hold completely in the beef packing industry. If these restrictions do not hold, then a serious loss of information occurs when the data are aggregated across temporal or spacial dimensions (Zellner and Montmarquett), leading to higher variances of empirical estimates and lower power of statistical tests. Within the context of industrial organization research, any statistical test for the presence of market power may be inaccurate when using aggregated data.

The direction and magnitude of the errors resulting from the inappropriate use of aggregate data are not known. For example, it is possible that empirical tests using aggregated data may indicate that firms are exercising market power when they are actually behaving competitively. Conversely, it is possible that market power may not be detectable using aggregate data when in fact individual decision makers are behaving in a non-competitive manner.

It is not difficult to understand why studies have proceeded using data aggregated over the various dimensions. Detailed firm-level data are confidential in nature and are difficult to obtain. This study is not intended to be a criticism of previous work that has used aggregated data. Rather, the goal of this study is to provide a guide for future applied work using econometric methods to analyze firm behavior, for policy formation, or for monitoring purposes by regulatory agencies such as the Packers and Stockyards Administration (PSA).

Model specification also plays an important role in the success of any econometric effort to test for market power. There is a potential for biased parameter estimates if the economic models are not specified such that they adequately capture the underlying technology of the industry being studied. It is possible that any error in modeling the technology will influence in an unpredictable manner the market power parameter in efforts to test for market power. Therefore, when modeling firm behavior, it is important to use a functional form that is flexible enough to accurately capture the underlying technology of the industry being studied. This study compares three alternative functional form specifications with regard to their ability to accurately model the underlying cost structure of the industry when testing for oligopsony power.

Policy Implications

In order to enforce the current interpretation[4] of antitrust laws and regulations, and to assist in further antitrust policy development, it is imperative that analysts and policy makers be able to accurately identify non-competitive pricing behavior when it is present. The efficiency and effectiveness of government policies and attempts to prosecute industry participants perceived to be operating in a non-competitive manner relies on the ability to accurately identify those industries or individual firms which are, in fact, exercising market power. If empirical tests of market power are to be used in monitoring the industry and for antitrust enforcement, it is important for policy makers to be confident regarding the accuracy and robustness of the results of those tests. If the results of these empirical tests are misleading and inappropriate policy decisions are made, a societal welfare loss could occur. The empirical techniques used to test for market power are relatively new and continue to be refined. It is therefore not clear how reliable the results are when using alternative levels of data aggregation and alternative model specifications.

The results of this study will provide insights regarding the need for, and importance of, obtaining detailed and mostly confidential firm-level, or even plant-level, primary data when testing for market power. Obviously, this has broad implications for the role of government as the move from a regulatory environment to a monitoring environment continues. There may be a need to ensure monitoring agency access to detailed firm-level

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[4]Currently, most analysts agree there is increased emphasis on micro-efficiency and firm behavior arguments in the enforcement of antitrust laws. This is in contrast to previous policies of intense scrutiny and possible regulation of industries which were highly concentrated. The change in antitrust policy has resulted in a severe reduction in antitrust activity in recent years (Preston and Connor).

data in industries which are perceived to have high potential for market power. Of course, there may be a tradeoff between the accuracy and power of statistical tests on the one hand, and the high cost of obtaining better data on the other. Therefore, it is important to determine which dimensions of aggregation and which model specifications have any potential to bias results so that decisions regarding data collection and model specification can then be made from a better informed position.

<u>Objectives</u>

The objectives of this research are:

1. To review the literature regarding the development of conjectural variations models of firm behavior within the New Empirical Industrial Organization (NEIO) framework;

2. To analyze the effects of data aggregation over firms and over time, and the effects of alternative model specifications, on empirical estimates of market power in the U. S. beef packing industry; and

3. To provide alternatives and suggestions regarding data needs and model specifications to help guide policy makers and analysts as they formulate and administer antitrust policies and monitoring procedures.

LITERATURE REVIEW

The amount of literature in this area is large. It is important that the reader understand the origination and development of the econometric modeling efforts involving conjectural elasticities that are designed to provide empirical estimates of the pricing behavior of market participants. This the "NEIO framework" referred to in Objective 1 above.

<u>Recent History Of Industrial Organization</u>

Until the late 1970s and early 1980s, industrial organization researchers -- and policy makers -- relied heavily on the Structure-Conduct-Performance (SCP) paradigm. The origination of this paradigm is often credited to Joe Bain, though Bain himself gives Edward Mason credit for the theory (Bain, 1972). The framework involves searching for empirical associations between market characteristics (structure), market conduct, and market performance (Bain 1942, 1968). The long term structural characteristics of an industry or sector include buyer and seller concentration, product differentiation, and barriers to entry. According to Bain, market conduct can encompass two aspects of behavior. The first includes any collusive mechanisms which industry participants might use to obtain coordination of their price and output policies with those of their rivals. This aspect of behavior is illegal under current U. S. antitrust laws. The second aspect refers to the firm-level, price-output calculation itself, which can include expectations of rivals' responses. This aspect of behavior is not necessarily illegal. Market performance is multi-dimensional, referring to such outcomes as prices, level of economic profits, progressiveness, and various other dimensions of market efficiency such as information availability (Bain 1960).

The SCP paradigm has proven to be a useful tool to help identify and target industries with the highest potential for non-competitive behavior (Geroski 1988). These models are designed to detect and predict general associations between structure and performance, but are not designed to pinpoint the actual behavior of firms in a specific industry. Under the current interpretation of U. S. antitrust laws and regulations, non-competitive behavior must be shown to exist, or be expected to develop as a result of a merger, before enforcement action can be taken (Landis and Posner). In order to accommodate this need, Weiss suggested that after selecting a specific industry for investigation, researchers and antitrust authorities should rely on more detailed intra-industry case studies. Several variations of these single industry case studies have become popular in recent years (Cowling and Waterson and Bothwell *et al.*)

One variation of the industrial organization case study analyzes firm-level behavior by empirically estimating the firm's conjectural variations, or beliefs regarding rival responses. An equation (or equations) in an econometric model is (are) derived from the profit maximization problem of the firms in an industry. The model parameters are then estimated to determine the extent to which price differs from marginal cost.

This study examines two potential problems that arise in the practical implementation of the econometric conjectural variations or NEIO technique. The first relates to the use of aggregated data to infer firm level behavior, and the second relates to potential problems of model specification. The remainder of this section focuses on the early development of the conjectural variations model and on studies that have used this model to examine behavior in the meat packing industries.

The Conjectural Variations Model And Extensions

Bresnahan (1989) summarizes the econometric behavioral modeling approach as an attempt to use systematic statistical evidence to study single, or related, industries. The central focus is on firm behavior, or conduct. Iwata (1974) was the first to attempt to empirically test for oligopoly market power using a conjectural variations model. He defined the firm's conjectural variation as the change in the quantity supplied by other firms in an industry that a particular firm believes will result if it changes it's own output or supply. Iwata developed the conjectural variations model by deriving the profit maximizing first order condition of an oligopolist producing homogeneous goods as shown below. With profit (π) defined for each firm as revenue minus costs, the profit

$$p_i = p(D)*q_i - C_i(w_1,...,w_k,q_i)$$

function can be written as:

where p is the price of output, q_i is the output produced by firm I, D is total industry output $\left(D = \sum_i q_i\right)$ and C_i represents total cost and is a function of firm output and the input prices (w_i's). Differentiating the revenue portion of equation (1) with respect to firm output yields an expression for perceived marginal revenue:

$$mr_i = p + \frac{\partial p}{\partial D} * \frac{\partial D}{\partial q_i} * q_i$$

If $\dfrac{\partial D}{\partial q_i}$ is rewritten as $\sum_k \dfrac{\partial q_k}{\partial q_i} = 1 + \sum_{k\_i} \dfrac{\partial q_k}{\partial q_i}$, and specified as $(1 + \gamma_i)$, then the right hand portion of

$$p + \left(\frac{\partial p}{\partial D} * (1 + g_i) * q_i\right)$$

equation (2) can be rewritten as:

where γ_i is defined as firm I's conjectural variation. From the solution of the first order condition for profit

$$p + \frac{\partial p}{\partial D} * (1 + g_i) * q_i - \frac{\partial C_i(w_1,...w_k,q_i)}{\partial q_i} = 0$$

maximization, setting perceived marginal revenue equal to marginal cost results in the following equation:

If α is used to represent the price elasticity of demand, $\dfrac{\partial D}{\partial p} * \dfrac{p}{D}$, then equation (4) can be rewritten

$$p + \frac{1}{a} * \frac{p}{D} * (1 + g_i) * q_i - \frac{\partial C_i(w_1,\ldots w_k, q_i)}{\partial q_i} = 0$$

as:

With this derivation, Iwata demonstrated that if the above equation is rearranged with p isolated on the left hand side, the market price level is a function of the price elasticity of demand, marginal cost (mc), and the conjectural variation of each firm.

Iwata analyzed the Japanese flat glass industry, a highly concentrated industry composed of three large firms, for the period 1956 to 1965. Using a three-step sequential process, the author first estimated cost functions for each firm in the industry using semi- annual data on labor, capital, and a composite of all other inputs for each firm. He then estimated market demand functions for the two primary types of glass produced, window and plate. Finally, conjectural variations were estimated as a function of the elasticities of demand, marginal costs, prices, and

$$g_i = a * \frac{mc_i - p}{p} * \frac{D}{q_i} - 1$$

quantities. This was accomplished by rearranging equation (5) in the following manner:

where mc_i = marginal cost = $\dfrac{\partial C_i(w_1,\ldots, w_k, q_i)}{\partial q_i}$.

Estimates of marginal cost and elasticities of demand from the first two steps were used, along with prices and quantities, to estimate γ_i for each firm and each product using the time series of the data. The results of Iwata's study were inconclusive, a result which he attributed to poor estimates of both price elasticities and marginal costs.

Another often cited work that further developed the conjectural variation approach is a 1982 study by Appelbaum. This paper shows how production theory can be extended to a general class of oligopolistic markets with homogeneous goods. The perceived marginal revenue expression from equation (2) is multiplied by $\dfrac{p}{p} * \dfrac{D}{D}$

$$p + \frac{\partial p}{\partial D} * \frac{D}{p} * \frac{\partial D}{\partial q_i} * \frac{q_i}{D} * p$$

, and rearranged as:

By specifying $\_ = \dfrac{\partial p}{\partial D} * \dfrac{D}{p}$, as the inverse market demand elasticity, and $q_i = \dfrac{\partial D}{\partial q_i} * \dfrac{q_i}{D}$ as the conjectural elasticity, the first order condition from equation (5) can be rewritten as:

$$p(1 + \; \mathsf{q}_{i} \_) = \; mc_i$$

Market power is broadly defined by Geroski as the deviation of price (p) from marginal cost (mc). Therefore, when perceived marginal revenue is equal to price, market power is absent. When perceived marginal revenue is less than price (because ε from equation (8) is negative), there is some element of market power (Bresnahan 1982). The measure of market power is composed of two parts; the inverse demand elasticity (flexibility), and the conjectural elasticity.

The empirical test for the presence of market power involves estimating θ_i from equation (8) and testing whether or not it is significantly different from zero. Since marginal cost is not provided exogenously, but must be estimated, equation (8) is supplemented with input demand equations derived via Shephard's lemma from the cost function to yield a system of simultaneous equations. These input demand equations provide additional information for the estimation process, so the variance of the estimated cost function (and marginal cost) parameters is reduced.

When using industry aggregate data to test for market power via equation (8), the measure market power ($\theta \varepsilon$) is interpreted as the weighted average of the firm measures. In order to obtain an unbiased estimate of θ using industry aggregate data, firms must have linear and parallel expansions paths, implying that marginal costs are constant and equal across firms and that all firms employ constant returns to scale technology. Appelbaum shows that if this restriction holds, than the conjectural elasticities of all firms must be the same ($\theta_i = \theta_j = \theta$) in equilibrium.

Using annual industry aggregate data from 1947 through 1971, Appelbaum applied the model to four U.S. industries; rubber, textiles, electrical machinery, and tobacco. The three variable inputs assumed to be used were labor, capital, and an intermediate input and a generalized Leontief cost function was used to represent the technology in each industry. The conjectural elasticity (θ) was not estimated as a single parameter, but was specified as a function of the exogenous prices in the system and estimated using two stage regression techniques. Appelbaum concluded that oligopoly power has been exercised in the electrical machinery industry and in the tobacco industry, but not in the rubber and textiles industries.

Measuring Oligopsony Power

Schroeter (1988) showed how the Appelbaum dual technique can be extended to measure deviations from pure competition in input procurement markets if the inputs are used in fixed proportions to the output produced.

$$\mathsf{p} = p(D)^* q_i - w_1(D)^* q_i - C_i(w_2,\ldots,w_k,q_i)$$

The profit function from equation (1) is rewritten as:

where w_1 is the price of the fixed proportion (primary) factor, q_i now represents the quantity of the primary factor used by firm I, D represents both total market demand for industry output, expressed in terms of the quantity of the primary factor, and input supply of the primary factor. The first order condition for profit maximization can be

$$\frac{\partial \mathsf{p}}{\partial q_i} = p + \frac{\partial p}{\partial D} * \frac{\partial D}{\partial q_i} * q_i - w_1 - \frac{\partial w_1}{\partial D} * \frac{\partial D}{\partial q_i} * q_i = mc$$

expressed as :

Multiplying by $\dfrac{p}{p} * \dfrac{D}{D}$ and $\dfrac{w_1}{w_1} * \dfrac{D}{D}$, and rearranging yields:

$$p + \frac{\partial p}{\partial D} * \frac{D}{p} * \frac{\partial D}{\partial q_i} * \frac{q_i}{D} * p \; - \; w_1 \; - \; \frac{\partial w_1}{\partial D} * \frac{D}{w_1} * \frac{\partial D}{\partial q_i} * \frac{q_i}{D} * w_1 \; = \; mc$$

If θ_i and ε are defined as the conjectural elasticity and demand flexibility, and η is defined as the inverse supply

$$p * (1 + q_{i-}) = w_1 * (1 + q_i \mathsf{h}) + mc$$

elasticity (flexibility) in the primary factor market ($\mathsf{h} = \frac{\partial w_1}{\partial D} * \frac{D}{w_1}$), equation (11) can be rewritten as:

      The firm's conjectural elasticity divided by the elasticity of input supply provides a direct measure of oligopsony power. Schroeter used annual data from 1951 through 1983 to estimate the model parameters in an econometric system. The system consisted of the first order condition for profit maximization, input demand equations to increase the efficiency (reduce the variance) of the marginal cost parameters, an output demand equation to obtain an estimate of ε, and a fed cattle input supply equation for the beef packing industry to obtain an estimate of η. The firm was assumed to use the non-material inputs of labor and energy in addition to the material input of fed cattle to produce beef, and a generalized Leontief cost function was used to capture the technology. The results implied that the assumption of price taking behavior is not valid for the beef packing industry. Price distortions, or market power, in both input and output markets were present but at modest levels.

      A study by Schroeter and Azzam (1990) extended the technique of Schroeter (1988) to the case of a two product oligopoly/oligopsony. Their model included single product conjectures and cross product conjectures in both output markets and the two primary input markets. The authors applied their model to the U.S. meat packing industry, encompassing both beef production and pork production. Some firms in the industry own only beef plants, some only pork plants, and some firms in the industry are engaged in the processing of both. The two goods were assumed to be related on the demand side, and were assumed to be produced in fixed proportions to the inputs of live cattle in beef processing and live hogs in pork processing. Schroeter and Azzam hypothesized that the extent of joint production identified suggests that firm's conjectures regarding cross market responses play a significant role in the profit maximization problem.

      Demand and supply elasticities were obtained from exogenous sources, not estimated within the model. Production was assumed to require five non-material inputs consisting of three types of labor, energy, and transportation services. The technology was represented by a generalized Leontief cost function. Quarterly industry aggregate data regarding input and output prices and quantities for a 10 year period were used for the analysis. Anticipated cross market conjectures were found to have no impact on the firm's profit maximization decisions. Single product conjectures were, however, found to be significant. The authors concluded that this was an indication of the presence of some market power in both beef processing and pork processing.

      Azzam and Pagoulatos (1990) pointed out that since the cost function is dependent upon the prices of inputs, deriving an expression for the conjectural elasticity in a factor market using the approach of Appelbaum (1982) is not possible unless, as in Schroeter (1988), one assumes Leontief technology for the input that is purchased in a market suspected to be non-competitive. Azzam and Pagoulatos propose an alternative primal approach, with technology described by a production function. In this framework, conjectural elasticities can be derived for output as well as for each input for which potential for market power is suspected, and these inputs are not restricted to be used in fixed proportions to the output.

      The derivation of the behavioral equations begins from the profit function expressed as:

$$p_i = p(D)*q_i - \sum_{j}^{n} w_j\left(X_j \right)* x_{ji} - \sum_{k}^{m} w_k * x_{ki}$$

where as before D represents total industry output ($\sum_{i} q_i$), x_{ji} is the amount of the non-competitive input j used by firm I, $X_j = \sum_{i} x_{ji}$ is the total industry demand for input j, and x_{ki} is the amount of the competitive input k used by firm I. For each non-competitive input, the first order condition, $\dfrac{\partial p_i}{\partial x_j}$, equating marginal value product

$$p*\frac{\partial q_i}{\partial x_j} + q_i*\frac{\partial p}{\partial D}*\frac{\partial D}{\partial q_i}*\frac{\partial q_i}{\partial x_j} = w_j + x_{ji}*\frac{\partial w_j}{\partial X_j}*\frac{\partial X_j}{\partial x_j}$$

with marginal factor cost is:

Expressing the marginal product of x_j ($\dfrac{\partial q_i}{\partial x_j}$) as f_j and multiplying the left hand side of equation (14) by $\dfrac{D}{D}$,

$$p*f_j*(1 + \frac{\partial p}{\partial D}*\frac{D}{p}*\frac{\partial D}{\partial q_i}*\frac{q_i}{D})$$

results in the following expression for marginal value product:

As before, the demand flexibility $\dfrac{\partial p}{\partial D}*\dfrac{D}{p}$ can be expressed as ε, and firm I's conjectural elasticity in the output market $\dfrac{\partial D}{\partial q_i}*\dfrac{q_i}{D}$ can be expressed as θ_i.

The right hand side of equation (14) is multiplied by $\dfrac{X_j}{X_j}$, resulting in the following expression for

$$w_j*(1 + \frac{\partial w_j}{\partial X_j}*\frac{X_j}{w_j}*\frac{\partial X_j}{\partial x_{ji}}*\frac{x_{ji}}{X_j})$$

marginal factor cost:

Firm I's conjectural elasticity in the X_j non-competitive input market ($\frac{\partial X_j}{\partial x_{ji}} * \frac{x_{ji}}{X_j}$) can be expressed as ϕ_{ij}, and

the supply flexibility in the X_j market ($\frac{\partial w_j}{\partial X_j} * \frac{X_j}{w_j}$) can be expressed as η_j. The first order condition (equation

$$p*(1 + q_{i-})*f_j = w_j*(1 + \Phi_{ij}h_j)$$

14) for each non-competitive input can be expressed as:

$$p*(1 + q_{i-})*f_k = w_k$$

For each competitive input, the first order condition, $\frac{\partial p_i}{\partial x_k}$, is:

In this primal approach to econometrically testing for market power, these behavioral equations (one for each input) are estimated in a simultaneous system along with a production function. As in the dual approach, the demand flexibility (ϵ) and the non-competitive input market supply flexibilities (η_j's) can either be provided exogenously, or additional equations can be added to the system to estimate these parameters simultaneously in the econometric model.

Azzam and Pagoulatos applied the model to the U.S. meat packing industry using annual aggregate industry data from 1959 through 1982. Technology was represented by a translog production function. The hypotheses of competition in both input and output markets were soundly rejected. The authors were apparently aware of possible data aggregation problems since they pointed out that until firm level data are available, little is known about how the market power estimates may by biased by aggregation.

Schroeter and Azzam (1991) added an additional dimension to the problem of econometrically estimating conjectures by exploring the connection between output price uncertainty and marketing margins in an oligopoly/oligopsony setting. The specific case they analyzed was the U.S. hog packing industry. The technique used was similar to that of Schroeter (1988), based on the Appelbaum dual model. They specified the expected margin in the industry as the sum of marginal cost, oligopoly price distortions, and oligopsony price distortions. An additional term was added in an ad hoc manner to the first order condition (equation 12) to account for risk aversion, with risk being measured by the standard deviation of output price.

Their total model consisted of a margin equation (first order condition), an input supply relation, and a demand relation. Technology was represented by a generalized Leontief cost function with inputs of labor, energy, and transportation services. Quarterly aggregate industry data from the second quarter of 1972 through the fourth quarter of 1988 were used for estimation. Oligopoly and oligopsony price distortions were found to be small, but statistically different from zero. Since the conjectural elasticity (θ) was specified as a function of exogenous variables, the price distortion could be calculated for each period. Oligopsony price distortions were prevalent early in the sample period; however, no statistically significant distortions were found in the later years. An important finding of this study is that when the price risk term was excluded from the model, the market power terms became significant and were more important determinants of the margins. Therefore, the authors concluded that ignoring the price risk component in empirical analysis can lead to erroneous inferences of non-competitive conduct.

In an attempt to identify factors that may mistakenly be identified as market power in behavior models, Stiegert *et al.* (1993) examined how the cattle price markdown ($\theta\eta$ from equation 12) is affected by both

anticipated and unanticipated supply shocks. Their hypothesis is that when packers cannot secure the average processing cost minimizing quantity of cattle, the packers may price (procure) cattle below marginal value product in order to avoid losses. The oligopsony models discussed previously would attribute this to market power.

The authors derived supply and input demand equations for the beef packing industry from a generalized Leontief profit function. The market power term in their model was specified as a function of both forecast and unanticipated cattle supply. Unanticipated cattle supply is measured as the difference between forecast supply and actual slaughter. Quarterly data from 1972 through 1986 were used for estimation, with factors of production being cattle, labor, and energy.

Stiegert *et al.* found packer behavior to be consistent with rule of thumb pricing for live cattle. As the anticipated live cattle supply decreased, the packers increased their markdown of live cattle prices. The authors arrived at the interesting conclusion that the measure that has traditionally been attributed to market power may not be market power at all, but rather supply shortages. These shortages may force packers to deviate from the minimum point on their average processing cost curve because there simply are not enough live cattle available for slaughter during some time periods.

Azzam and Schroeter (1991) argued that a problem of previous studies of competitive behavior in the beef packing industry is that they have not taken into account the regional nature of fed cattle procurement. Their paper proposed a non-econometric equilibrium approach for projecting price effects. The equilibrium conditions are derived in the same manner as those used in the econometric behavioral studies of Schroeter (1988) and Schroeter and Azzam (1990). Packers were assumed to choose cattle input quantities to maximize profit. A firm with market power will internalize the effect of that choice on regional quantity, and in turn on price. The authors derived a relationship between the price-cost margin in the regional market, and a function involving an index of the degree of coordination in the region, the regional Herfindahl index, and the regional supply elasticity in fed cattle. Basically, this function replaced the $(\theta\eta)$ term outlined in the first order condition derived by Schroeter (1988) in equation (12).

With the objective of determining how recent or future increases in concentration have affected or will affect cattle prices, the authors simulated results beginning with a baseline case consistent with the conditions in the industry at the time of the study. The parameters of the simulation model were then varied, and the model recalculated for each variation. For instance, concentration ratios within regions were increased, and conduct indices were varied to reflect more cooperative behavior. It was shown that for fixed values of the coordination index and supply elasticity, the price distortion increased with increases in concentration. Also, for given conduct and concentration, the distortion decreased as supply elasticity increased.   The authors reported that it is likely that cattle prices have been depressed by less than one percent in the most concentrated regions relative to what would have occurred in the competitive ideal. The magnitude of this estimate was less than that of previous estimates of fed cattle price distortions due to oligopsony power.

A 1993 study by Koontz *et al.* was an attempt to go beyond the identification of conduct. The motivation for the study was the fact that little attention had been paid to understanding the optimal pricing strategies in an oligopoly/oligopsony setting. An additional motivation was the desire to account for the regional nature of fed cattle markets. The study is unique in that it tried to model firm conduct in terms of non-cooperative game theory.

Short-run (daily) beef packer behavior was modeled by assuming that in this very short run, everything is fixed except for the number of fed cattle slaughtered. A trigger pricing strategy based on margins in the previous period was assumed under the theory that packers recognize the choice between pricing to maintain market share and pricing to improve profit margins. The authors derived a multi-period optimization problem which contained market power measures. These market power (conduct) measures were allowed to switch between the choice of cooperation or non-cooperation among and across firms. The choice was triggered by a decision rule based on previous period margins.

Daily prices from four U.S. regional markets were collected and used for estimation. Depending on the region, the authors found market power gains of from $5.00 to $19.00 per head during an early period (1980 - 1982). The market power gains were lower, $2.00 to $5.00 per head, during a more recent period (1984 - 1986). The decrease in the exercise of pricing power during the later period was due to a decrease in the probability of being in the cooperative phase of the game. A conclusion reached that is particularly relevant for this study is that the magnitude of the conjectures in this study using daily data were smaller than estimates from other studies using

data aggregated over time. The authors found that market power in this industry is not constant over time, nor is it constant over geographical areas.

Summary

The goal of most empirical NEIO behavioral studies is to attempt to measure market power. This chapter has revealed that while there are many ways to go about achieving this objective, many questions remain unanswered. For example, several studies (Schroeter and Azzam 1991, Stiegert *et al.*) reveal that there is a real danger that the effect of factors excluded from the model will be attributed to market power. In addition, the consequences of using aggregated data to test for market power within this framework are not known. The assumptions required for aggregation to be possible without biasing results have been pointed out in some of the studies reviewed in this section, and will be further discussed in the next section. The magnitude of the possible error in estimation when using aggregate data to study industries in which assumptions allowing aggregation of data are violated has not been determined. Finally, empirical estimates of market power may also be biased due to model misspecification. The use of incorrect functional forms to represent processing technology may lead to incorrect conclusions regarding the presence or absence of market power. These aggregation and choice-of-functional-form issues and how they might impact the effectiveness and correctness of the conjectural variations model approaches to testing for market power are pursued in detail in later sections.

THEORY BEHIND THE TESTS

Empirical tests for market power must be developed and applied within a theoretical framework. Without understanding of profit maximizing behavior and the theory which encompasses that behavior, tests for market power are difficult if not impossible to interpret.

Modeling Oligopsony Behavior In U.S. Beef Packing

For this study, it is assumed that beef packers can potentially exercise market power in the procurement of fed cattle. The beef packing industry is assumed to use the variable inputs of labor, energy, and other materials to produce output (boxed beef) in direct proportion to the number of fed cattle slaughtered. The fixed proportion (dressing percent) on average remains constant across firms and over time, though it can vary somewhat between individual animals. Beef packing firms have large investments in plant and equipment which cannot be easily altered from week to week. For this study, this investment is assumed to be a fixed input (capacity) in processing fed cattle. Packers purchase fed cattle in regional procurement markets which tend to be highly concentrated (Ward 1988). The output of the beef packing industry is sold in a national market, which is less concentrated than the fed cattle procurement markets. For this study, it is assumed that this output market is competitive. The assumption of a fixed input[5] and the assumption of a competitive output market distinguish the models developed for this study from that of Schroeter (1988).

$$ \text{Max} \, \pi \; = \; \gamma \, P_y * y_i \; - \; w_1(Y) * y_i \; - \; VC(\, w_2, \ldots, w_4, K_i, y_i \,) $$

The firm level profit maximization problem for beef packers can be expressed as:

where P_y is the output price, γ is the dressing percentage[6], y_i is the fed cattle slaughter of firm I, Y is the total regional fed cattle slaughter ($\sum_i y_i$), w_1 is the regional price of fed cattle, VC represents variable processing cost,

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[5]This study treats capacity as a fixed input and uses a short run cost function. Previous studies have treated capital as a variable input.

[6]γ is assumed to be a constant for this study. For the remainder of this chapter γP_y is expressed as simply P_y, which is used to represent the price of output as adjusted by dressing percentage.

w_2 through w_4 are the input prices of labor, energy, and materials, and K_i represents the capital stock (capacity) of firm I. Differentiating equation (19) with respect to y_i yields the first order condition for profit maximization,

$$\frac{\partial p}{\partial y_i} = P_y - w_1 - y_i * \frac{\partial w_1}{\partial Y} * \frac{\partial Y}{\partial y_i} - \frac{\partial VC}{\partial y_i} = 0$$

expressed as :

$$P_y - w_1 * (1 + \frac{\partial w_1}{\partial Y} * \frac{\partial Y}{\partial y_i} * \frac{y_i}{w_1}) - \frac{\partial VC}{\partial y_i} = 0$$

which can be rewritten as:

      As discussed earlier, previous researchers have expanded the market power term, $\frac{\partial w_1}{\partial Y} * \frac{\partial Y}{\partial y_i} * \frac{y_i}{w_1}$, into

two components, $\frac{\partial Y}{\partial y_i} * \frac{y_i}{Y}$ and $\frac{\partial w_1}{\partial Y} * \frac{Y}{w_1}$ (θ_i and η from equation 12). This representation has been termed a conjectural elasticity times the fed cattle supply price flexibility. This breakdown demonstrates that in the oligopsonistic setting the behavioral equation (first order condition) for each firm includes the firm's conjectures regarding industry responses (Kamien and Schwartz), and implies that conduct is an important determinant of performance with regard to pricing (Geroski).

      Given that $Y = \sum_i y_i$, the fed cattle price (w_1) is a function of Y, and that each firm's procurement decision depends on the firm's conjectural variation [see equation (21)], the fed cattle market equilibrium price and quantity depends on the complete set of conjectural variations held by all producers in the industry (region). Econometric models of firm behavior attempt to assess the value of these conjectures (or the conjectural elasticities $q_i = \frac{\partial Y}{\partial y_i} * \frac{y_i}{Y}$) to infer firm behavior along the spectrum from competitive to monopsonistic (monopolistic).

      Theoretically, one should be able to separately estimate both θ_i and η. However, in order to explicitly estimate θ_i, one must obtain an estimate of η. This may be accomplished by providing a supply flexibility (or elasticity) exogenously, or simultaneously estimating both η and θ_i. By explicitly estimating θ_i, one can test whether θ_i is equal to zero. This is strictly a test of the conduct of setting price equal to marginal cost (Appelbaum 1979). From a practical point of view, it is difficult to obtain a consensus regarding the estimate of the supply flexibility in many markets. Any error in estimation of η would bias the estimate of θ_i. By the same token, inclusion of an erroneous exogenous estimate of the supply flexibility would bias the estimation of the market conduct parameter (θ_i).

      To reduce the potential estimation bias, an alternative test for market power estimates the $\theta_i \eta$ term as one parameter and then tests whether this parameter is equal to zero. This is a test of one of the following three scenarios: 1) $\theta_i = 0$ and $\eta \neq 0$, 2) $\theta_i \neq 0$ and $\eta = 0$, or 3) $\theta_i = 0$ and $\eta = 0$. Any one of these combinations would result in the entire term ($\theta_i \eta$) being equal to zero. To clarify, the η in the term $\theta_i \eta$ could be non-zero (the firm faces a positively sloping supply curve in reality), but the firm may not realize this potential to influence the input price. In their profit maximization decision, the firm may behave as if it faced a horizontal supply curve, and

treat the price of the input (cattle) as fixed. This model specification is designed to identify market power by

testing whether or not the whole market power term $[\frac{\partial w_1}{\partial Y} * \frac{\partial Y}{\partial y_i} * \frac{y_i}{w_1}$ from equation (21)] is equal to zero, but is

not designed to determine the specific industry conduct in terms of behavioral theories. Using this approach to testing for market power further distinguishes this study from previous research.

In an empirical study using a time series of disaggregate firm-level data, one could model each firm separately and estimate the market power term for each decision making unit. For this particular experiment, numerous estimates of market power (one θ_i for each plant or firm) when using the disaggregate firm-level data would be difficult to compare with the one estimate of market power (θ for the whole industry) when using industry aggregate data. What is needed for this study is a simple test to reveal the exercise of market power in the industry that can be used in both the disaggregate cases (using pooled time series - cross sectional data), and in the aggregate cases (using only time series industry level data), so that the results can be compared.

Previous studies using industry data have restricted their estimate of the conjectural elasticity (θ), the portion of the market power term that could differ across firms, to be either constant across firms (Borooah and Van Der Ploeg), or to be a weighted average of each firm's conjectural elasticity (Appelbaum 1982, Bresnahan). For this study, A similar assumption is imposed in that the first component of the market power term from equation

(21) $(\frac{\partial w_1}{\partial Y} * \frac{\partial Y}{\partial y_i})$ is assumed to be constant across plants. This implies that changes in procurement will result

in the same proportional changes in fed cattle prices, regardless of which plant (firm) initiates the procurement (output) change. This assumption allows the specification of a market power term that can be used in both the disaggregate and aggregate cases. Total exercise of market power is allowed to differ between plants or over time

as procurement levels change since the second part of the market power term ($\frac{y_i}{w_1}$) is allowed to vary across plants

$$ a_0 * \frac{y_i}{w_1} $$

and over time. With these assumptions the total market power term can be expressed as:

with $\alpha_0 = (\frac{\partial w_1}{\partial Y} * \frac{\partial Y}{\partial y_i})$ being constant across plants (firms). In the aggregate cases y_i is replaced by it's aggregate

counterpart (Y), allowing the total amount of market power in the industry to depend on the level of industry input procurement.

With the specification of the market power term described in the last section, the first order condition

$$ P_y - w_1 = a_0 * y_i - \frac{\partial VC}{\partial y_i} $$

from equation (21) (the behavioral equation) can be rewritten as:

The technical relationships underlying the true variable cost function are not known. Therefore, a functional form must be chosen to represent the variable cost function and it's parameters need to be estimated along with the parameter which captures the degree of market power (α_0). In previous studies, factor demand (or share) equations have been added to the econometric model in a systems approach to supplement the specification

of marginal cost in equation (23) and increase the efficiency of the cost function parameters. In the models to be used for this study, the cost function itself will be included in the system to add additional information to the estimation process and further help to obtain the cost function parameters. Therefore, for this study, each system will include the behavioral equation, the cost function itself, and the factor demands or share equations (derived from Shepard's lemma).

$$P_y - w_1 = a_0 * y_i - \frac{\partial VC}{\partial y_i}$$

Each specification of the model will consist of the following equations:

$$VC = VC(w_2, ..., w_4, K_i, y_i)$$

$$x_j = \frac{\partial VC}{\partial w_j} \quad or \quad \frac{x_j * w_j}{\sum_j x_j * w_j} = \frac{\partial VC}{\partial w_j} * \frac{\sum_j x_j * w_j}{w_j}$$

and for each input j:

Previous studies of market power in the meat processing industries have typically used the generalized Leontief functional form to represent the industry cost function (Schroeter and Azzam 1990, 1991, Schroeter, Stiegert *et al.*). These researchers have assumed that the generalized Leontief is an adequately flexible form to capture the true cost structure of the industries being studied. This assumption has not been tested. For this study, another interesting dimension of empirical estimates of market power using NEIO econometric methods will be investigated by using the generalized Leontief, translog, and normalized quadratic functional forms to represent the firm/industry cost functions. This will allow investigation of not only the effects of data aggregation, but also the impact of using different functional forms on parameter estimation.

Data Aggregation

A common problem faced by researchers analyzing agricultural or agribusiness markets is that the available data are aggregated over various dimensions. These dimensions commonly include aggregation over space or firms, aggregation over time, or aggregation over inputs in the production process. The data are often aggregated to such a degree that the actual underlying decision process which the researcher is trying to model may be undetectable in the data (Zellner and Montmarquett). Failure to account for the effect of this data aggregation can result in distorted parameter estimation in empirical work (Robinson, Ward 1992, and others), and could bias the views of industry analysts and policy makers.

This research determines the effects of data aggregation over plants or firms and over time on econometric estimates of market power in the beef packing industry using the behavioral model discussed in the last section. This section presents a discussion of the requirements for legitimate aggregation over various dimensions, and why the requirements do not likely hold in data aggregated over plants (firms) or over time in the beef packing industry.

In general, data aggregation leads to a loss of information that may cause inflation of error variance and a worsening of multicolliniarity between variables in statistical modeling (Houck). The magnitude of this information loss, and the resulting loss in efficiency of the estimates, depends not only on the level of aggregation, but on the nature of the variables themselves. Therefore, it is nearly impossible to predict the consequences of

aggregation in any given situation. Consequently, most studies of the aggregation issue have been case specific. These studies are either deterministic, in that they identify the consequences of aggregation of one specific data set (Young and Stevens, Park and Garcia, Blank and Schmiesing), or like this study, attempt to assign probabilities to the consequences of aggregating data in a particular empirical context (Orcutt *et al.*, Sexaur, Choi).

In empirical work, the aggregation problem can arise when it is necessary to use simplified models as mathematical approximations to economic theories (May). Some researchers have identified aggregation problems as being similar to measurement error (Hannan), while others have viewed aggregation as a specific type of specification error (Grunfeld and Griliches). In a regression context, the variation in the dependent or independent variables may be altered by the aggregation in such a way that the influences of the independent variables can become intermingled. This can make accurate analysis in a regression framework difficult or impossible (Hannan).

The link between the level of data aggregation and the model specification, both chosen by the researcher, should not be ignored. The performance of a particular model specification may be sensitive to the units of observation in either a spacial context (Lyon and Thompson), or in a temporal context (Blank and Schmiesing, Lancaster). Following Lyon and Thompson, this study investigates the effects of both *aggregation over firms and aggregation over time* in a particular empirical context (market power in beef packing) using alternative model specifications.

The use of aggregate data implies that certain assumptions must hold in order to estimate both cost function parameters and the measure of market power. When using aggregate data to estimate cost function parameters, the researcher believes that the assumption of constant and identical marginal costs for all firms (if aggregating spatially) or over time (if aggregating temporally) holds. The individual cost functions must be of the Gorman Polar form (Warmon and Sexton), implying that the production expansion paths must be linear and parallel (Appelbaum 1982). One of the practical motivations for this study is that this assumption may be too restrictive with regard to the beef packing industry. Previous researchers have identified long run economies of size in this industry (Ward 1988 and Duewer and Nelson). We know that productive capacities are not the same, and therefore cannot assume that all firms have the same cost structure. If the assumption of constant marginal cost does not hold, the estimates of cost function parameters obtained using aggregate data will be biased relative to those obtained using weekly firm-level data. In addition, the market power measure is assumed to summarize the information regarding conduct and performance of the units being studied when using spatially aggregated data. As with the estimates of cost function parameters, if the implied assumption of identical marginal costs does not hold, then measures of market power obtained using aggregate data may be biased relative to measures obtained using disaggregate data (Lopez and Dornsainvil).

In order to *aggregate several inputs* into a group for econometric modeling purposes, one must assume that those inputs are weakly separable from all other inputs. This means that the marginal rate of substitution between any two inputs in the group to be treated as an aggregate cannot depend on the level of input usage from any other group. For example, to combine skilled and unskilled labor into one aggregate labor variable, the marginal rate of substitution between these two inputs must not depend upon the level of any input from another group, such as energy. For this study, it is assumed that the aggregate input groups of capital, labor, energy, and other materials meet the separability requirements when analyzing the beef packing industry. Previous studies of the meat packing industry have used similar input groupings (Schroeter 1988, Schroeter and Azzam 1990, 1991), and these input classes are intuitively distinct.

Any attempt to include more disaggregated measures of input usage would make the study unmanageable in terms of model specification and the number of observations needed in each data set to allow sufficient degrees of freedom for statistical testing. Therefore, it is beyond the scope of this study to empirically test the imposed separability assumptions. It should be noted, however, that if these assumptions do not hold, there is a potential for biased results. Burgess, for example, found that the maintained hypothesis of separability between factors in some previous studies had been responsible for imposing a downward bias on derived demand elasticity estimates. In addition, using non-parametric tests Lim and Shumway determined that the justifiable levels of input aggregation in agricultural production data varies widely between sectors and geographical areas being studied.

Summary and Conclusions

Many empirical studies of agricultural and other markets continue to use aggregated data, suggesting that researchers are largely ignoring implications of using such data. This is not necessarily the result of poorly planned research. In most cases, the choice is made based on data availability (Hannan). Nonetheless, there may be

hazards associated with using data simply because they are the best or only data available (Houck). There is an overwhelming consensus among previous empirical studies that changes in the level of data aggregation produce changes in parameter estimates. In some situations, the bias has been found to be small (Boot and Dewit), inferring that the level of data aggregation in some instances may not be a big issue. In other situations (Eisgruber and Schuman, Hannan), the aggregation bias has been so large that the authors have reached the strong conclusion that estimates obtained from aggregated data are not very useful for economic analysis.

The concept of fragility refers to whether conclusions drawn from a modeling effort are sensitive to changes. These changes can be in the form of assumptions, model specification, or data (Zellner and Montmarquett). Hannan notes that there is a need to consider the magnitude of errors and faulty inference associated with using aggregate data under various situations, and Lyon and Thompson add that it is also necessary to investigate the impact of differing model specifications. In response, researchers have begun to empirically examine these issues on a case by case basis. This study will be an important contribution to this body of research, in that it will determine whether the results of conjectural variations behavioral models are fragile with respect to the level of aggregation, and/or model specification. If aggregation is found to be a problem, this would suggest the available research using the NEIO approach to search for market power may not be adequate for policy purposes, including regulatory and monitoring functions of federal agencies.

SIMULATING THE BEEF PACKING INDUSTRY
AND TESTING FOR MARKET POWER

In this section, a Monte Carlo experiment that explores the implications of using aggregated data to test for the exercise of market power in the U. S. beef packing industry is described. In the experiment, data are simulated to have characteristics representative of the beef packing/processing industry in two broadly defined geographical regions: the Northwest with plants in Washington and Idaho; and the Southern Plains with plants in Texas, Kansas, Colorado, and Nebraska. To make the experiment as useful as possible, underlying assumptions regarding the beef packing industry are varied in two dimensions, technology and behavior. Data are aggregated across firms, over time, or both to add a third dimension to the data generation process. In addition to exploring the issue of data aggregation, the sensitivity of estimates of market power to model specification is examined by comparing results from alternative functional form specifications.

Since the production technologies of beef packers are not known, it is necessary to perform the experiment across a range of plausible technologies, thus increasing the chance of closely replicating the true underlying technology and broadening the scope of the study. These technologies differ by important characteristics such as relative ease of factor substitution and returns to scale. There is a tradeoff between the breadth of the experiment and manageability of the study. In the study, 13 different technologies are simulated for each behavioral scenario.

There are a number of plausible assumptions regarding the behavior of industry participants. For instance, decisions could be made at the firm level, or each plant of a multi-plant firm could act as an individual profit center. The fed cattle procurement market could be competitive, in which case individual plants or firms would have no ability to exercise market power on the input procurement side, or there could be various degrees of potential for, and exercise of, market power in the industry. Five behavioral scenarios are designed to cover this scope of possibilities.

Lastly, there are a number of different levels of aggregation at which the data could be collected. Data could be collected from individual plants or from individual firms, encompassing weekly, monthly, quarterly, or some other observation time frame. On the other hand, aggregated industry level data could be collected representing any observation time unit. The three levels of data aggregation across decision makers and over time to be simulated and examined in this study are presented along with a brief discussion regarding the number of observations generated at each level of aggregation.

Monte Carlo experimentation involves repeating each technology/behavioral scenario/aggregation treatment a number of times (with some changes in the exogenous inputs) in order to assign probabilities to the outcomes. It is common for economists and statisticians to use this technique to discern the properties of various models or estimators (Smith).   For each treatment, the specific steps are to: 1) generate the data; 2) test for market power using the generated data; and 3) collect the outcomes of each test. Only the test outcomes are saved from each cycle.

A critical question that arises is how many times the experiment must be repeated for each treatment in order to infer a probability distribution from the outcome of the simulation. From a technical point of view, it depends on the magnitude of the dispersion of the stochastic input variables. The larger the variance of the stochastic variables, the more repetitions are needed to capture the distribution of the outcomes of the experiment. Previous researchers provide a practical guide to the number of replications needed (Reidy, Orcutt *et al*., Thursby and Knox Lovell, and others). Reidy varied the number of replications in a Monte Carlo experiment between 30 and 500. In general, his probability measures were not sensitive to changes in the number of replications above 30. There is clearly a tradeoff between the cost of resources used in producing more replications of each experiment and the resultant increase in the precision of the probabilities garnered from the simulation. Following Richardson and Condra, Nutt and Skees, and others, each treatment in this experiment will be replicated 100 times. When all treatments for the study are considered, the total experiment involves generating 6,500 different data sets at each of 3 aggregation levels, for a total of 19,500 unique data sets.

The specification of each of the econometric models used to test for market power in the generated data are presented later in this section. Three models are specified which will be used to test for market power at all levels of aggregation. These models differ in the functional form of the cost function used to capture the underlying technology of the industry.

The Experiment Detail

As mentioned above, there are three dimensions to the data generation process. First, 13 different technological possibilities for the U. S. beef packing industry are represented. Second, data for each technology are generated consistent with 5 alternative behavioral scenarios, amounting to different assumptions regarding the exercise of market power and the decision making level in the industry. Third, data sets for each technology/scenario combination are generated at 3 alternative aggregation levels. Each technology/scenario/ aggregation level combination represents a unique treatment, requiring the generation of 100 data sets for testing. Table I provides an overview of the 5 scenarios and the 3 aggregation levels. The remainder of this section reveals the details of the data generation process.

Assumptions Governing The Data Generation Process

For this study, it is assumed that fed cattle procurement decisions are made at either the plant or the firm level on a weekly basis. This is the same as deciding how much output to produce in a given week since output is assumed to be directly proportional to the volume of cattle slaughtered. Each plant is assumed to have some input such as capital (represented by maximum slaughter chain speed) that is fixed in the relevant decision making time frame. In addition to capital, the plants are assumed to use three general classes of variable inputs to process fed cattle into final products. These include labor, energy, and other material inputs. This choice of inputs is consistent with previous research. However, previous studies have

Table I. Overview of the scenarios, aggregation levels, and tests performed in the experiment.

Behavior Data Aggregation	Scenario 1. No market power	Scenario 2. Small amount of market power exercised	Scenario 3. Relatively large amount of market power exercised	Scenario 4. Firm, rather than plant is the profit center. Some degree of market power exercised	Scenario 5. Market power is possible, but plants do not recognize the potential for market power
Disaggregate data representing 52 weeks of plant level weekly data from two major beef packing regions in the U.S.					

For each of these scenario-aggregation level combinations the same 13 technology assumptions are looked at in a separate treatment, providing a total of 195 sub-experiments (treatments). Each treatment involves the simulation of 100 data sets at each level of aggregation. Each data set is tested for market power using the econometric models and the results of the tests are saved to

Data aggregated over all plants, firms, and both regions representing 52 weeks of industry level data.
Industry level data aggregated over time to represent 20 years of quarterly data.

lumped the energy and other material categories into one (Schroeter 1988, Azzam, and Pagoulatos), or have included transportation services instead of other material inputs (Shroeter and Azzam 1990, 1991). These three general categories of variable processing inputs (in addition to the primary input of fed cattle) are assumed to be sufficient to adequately represent the processing technology while maintaining manageability of the study. It is doubtful whether any comprehensive empirical study of the industry could ever accommodate more variable inputs because of statistical degrees of freedom limitations.

In order to estimate the systems of equations used to test for market power, the following data are needed: input quantities and prices (including regional cattle prices); output quantities and prices; and plant capacities. Some of the variables are provided exogenously, and the remaining variables are calculated consistent with profit maximizing behavior on the part of the plants or firms. This study uses a "primal" approach to simulate the data, with the production technology being represented by a production function. Input quantities and output price are provided exogenously, output is calculated, and input prices consistent with profit maximizing behavior are then obtained from the first order condition for profit maximization.

For realism, these generated data reflect the size distribution of beef slaughtering/processing plants in the two procurement regions chosen for this study. The first region, commonly referred to as the Southern Plains cattle feeding area, contains a total of 14 major beef packing plants belonging to 4 firms in southwest Kansas, eastern Colorado, southern Nebraska, and the panhandle of Texas. The second region is the Northwestern U.S. cattle feeding area where there are 4 major packing plants belonging to 3 firms, all located in Washington and Idaho.

Variable input quantities for average plants in each size category and a categorical measure of capacity are provided for each plant in the two regions for which data are simulated. The plants are divided into three distinct size categories based on reported daily capacities (CF Resources). The categories are chosen arbitrarily, based on experience and PSA data and include small (under 2,000 head per day), medium (2,000 to 4,999 head per day), and large (over 5,000 head per day). At the end of 1993, there were eight medium sized plants and six large plants in the Southern Plains region. In the Northwest region, there were three small plants, and one medium sized plant. There were no large plants in the Northwest, and no small plants in the Southern Plains (CF Resources).

Generating Inputs And Outputs

The production function chosen to represent the relationship between input usage and the number of units of cattle processed (number of units of output produced) in the data generation process is a generalized CES (Mukerji). This functional form is chosen because of it's flexibility to represent a number of different technological possibilities with respect to elasticities of substitution and returns to scale. The exact specification of the generalized CES production function to be used for this study is:

$$Y = \left(\sum_i \mathrm{d}_i\, X_i^{r_i} \right)^{g/r}$$

In addition to it's general flexibility, the generalized CES has been shown to have globally well behaved curvature properties as long as the following parameter restrictions are imposed (Hanoch, Driscoll):

(1) $\delta_i > 0$.
(2) $\Sigma\, \delta_i = 1$.
(3) ρ and $\rho_i > 0$.
or $\rho < 0$, and $-1 < \rho_i < 0$.
or $\rho = \rho_i = 0$.

      Thus, the generalized CES is appealing for Monte Carlo experimentation because the characteristics of the production process (the technology) can be altered easily in any way desired by changing ρ_i 's, ρ, δ_i 's , and γ. For this study γ is set to 1 in all instances, and $\delta_1 = \delta_2 = \delta_3 = \delta_4 = .25$. Values for the remaining parameters for each of the 13 technologies are given in Table II.

Table II.   **Summary of the parameter values of the various technologies imposed on the data generation process, their associated returns to scale, and Allen cross price partial elasticities of substitution.**

		Parameter Values					Allen Elasticities of Substitution					
	rts[a]	ρ	ρ_1	ρ_2	ρ_3	ρ_4	12	13	14	23	24	34
1	1	.5	.5	.5	.5	.5	.67	.67	.67	.67	.67	.67
2	1	1.5	1.5	1.5	1.5	1.5	.4	.4	.4	.4	.4	.4
3	1	2	2	2	2	2	.333	.333	.333	.333	.333	.333
4	1	3.2	3.2	3.2	3.2	3.2	.24	.24	.24	.24	.24	.24
5	1.01	.8	.8	.8	.8	1.5	.558	.558	.402	.558	.402	.402
6	.97	2.9	2	3.2	3.2	3.2	.306	.306	.306	.218	.218	.218
7	.96	3.2	3.5	2.5	3.5	3.5	.26	.20	.20	.26	.26	.20
8	.98	1.9	2	1.8	2.15	1.85	.34	.303	.335	.325	.359	.319
9	1.01	1.5	1.4	1.8	1.45	1.7	.374	.427	.388	.366	.332	.379
10	.99	-1.1	-.2	-1.1	-.2	-.2	1.25	-.15	-.15	1.25	1.25	-.15
11	1.11	.45	.5	.5	.5	.5	.67	.67	.67	.67	.67	.67
12	1.21	.45	.4	.5	.6	.7	.74	.70	.66	.65	.61	.57
13	1.24	.35	.7	.6	.5	.4	.53	.56	.61	.60	.64	.69

[a] Returns to Scale

      Sufficient technological differences are achieved by varying the values of ρ and the ρ_i's. An effort is made to keep the returns to scale parameter close to 1 for the first 10 technologies in order to concentrate on changes in assumed input substitutability, but to allow for increasing returns to scale in the last 3 technologies.[7]

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[7] The values of ρ and the ρ_i's were arrived at through the use of a spreadsheet which calculated the returns to scale via the formula in Driscoll, and the Allen partial elasticities via the formula in Mukerji.

Technologies exhibiting long run economies of scale are included since both Ward (1988) and Duewer and Nelson found existence of long run economies of scale in the beef packing industry.

The first 4 technologies from Table II are homogeneous CES, and the substitution possibilities between inputs are made increasingly difficult as one moves from technology 1 to technology 4. Technology 4 is very near Leontief technology. For technologies 5, 6, and 7, the elasticity of substitution is one value for three input pairs and another value for the remaining three input pairs, with different values and combinations for each of these three technologies. In general, the substitution possibilities become more difficult moving from technology 5 to technology 7, and technology 7 is fairly close to a Leontief technology. Technologies 8 and 9 exhibit a unique elasticity of substitution for each input pair, and these values differ between the two. Technology 10 assumes that capital, energy and materials are slight complements to one another, but are all moderately substitutable for labor. The last 3 technologies are not homogeneous and exhibit increasing returns to scale. Technology 11 is CES, and technologies 12 and 13 have different substitution elasticities for each input pair. These technologies were chosen because they represent a fairly broad range of input substitution and returns to scale possibilities.

The input variables (X_i's) are randomly drawn from a multi variate log-normal distribution. For each of the 3 size categories of beef processing plants, the mean values of the capacity and input quantity variables used in this analysis are provided in Table III.

Table III. **Mean values of capacity and weekly variable input quantities assumed to be used in the respective size categories of beef packing plants.**

	Under 2,000 hd/day	2,000 - 5,000 hd/day	Over 5,000 hd/day
Chain Speed	82,500	191,000	302,500
Labor	16,000	35,000	52,000
Energy	1,500	3,120	4,700
Materials	1,000	2,300	3,600

The assumed variance - covariance matrix of the multi variate log-normal distribution of inputs is provided in Table IV.

Table IV.   **Variance - Covariance matrix associated with the input usage matrix.**

	Chain Speed	Labor	Energy	Materials
Chain Speed	0	0	0	0
Labor	0	0.00664	0.0073	0.0077
Energy	0	0.0073	0.0124	0.0099
Materials	0	0.0077	0.0099	0.0124

The capacity variable (chain speed) is assumed to be fixed in the short run and does not have an associated covariance with any other input. It is assumed that labor usage can vary as much as 15 percent, and energy and materials inputs can vary as much as 20 percent from mean values. This is based on the observation that plants rarely operate less than a 32 hour per weekly shift work week, about 20 percent less than the standard 40 hour shift, but may also kill on Saturday which could add approximately 20 percent to the normal shift work week. However, included in the labor component are salaried and management personnel, a component which does not vary nearly as much as the shift labor. Therefore, it is assumed that the total labor input could typically vary by as much as 15 percent from week to week during normal operation.   The other broad categories of inputs are assumed to vary by about the same amount as the shift labor, in large part due to the assumed high correlation between the use of the various inputs.   For example, the correlation between labor and energy and the correlation between energy and materials are both assumed to be .8. The correlation between labor and materials is assumed to be .85. This is simply based on the observation that energy would be used even when the plant is shut down or operating at a level far below capacity. However, labor and materials are both assumed to be used in close to fixed proportions to the number of cattle being slaughtered. For the entries in Table IV, the standard formula for covariance(i,j), $Cov(i, j) = r_{ij} * s_i * s_j$,[8] is used to obtain the individual entries.

In order to estimate the market power models, it is necessary to assume that there were some changes in plant capacity throughout the year for those treatments in which a year's worth of data are required and over the 20-year period for those treatments in which 20 year's worth of data are required. This is accomplished by assuming that certain plants increase capacity (move up 1 size category) periodically through the data simulation process. Specifically, at the end of the 5th year, 2 plants were assumed to increase capacity from the medium to the large category, and 1 plant was assumed to switch from the small to the medium category. At the end of the 10th year, 2 plants were assumed to change from the small to the medium category. At the end of the 15th year, 2 more plants were assumed to add capacity, going from small to medium classifications. In the final year (the only year used for disaggregate and industry level weekly data sets), at the end of the 1st quarter one plant increased in size from medium to large, at the end of the 2nd quarter one plant increased in size from small to medium, and one plant increased in size from medium to large. Finally, at the end of the 3rd quarter one small plant became a medium sized plant. These changes provide enough variability in the capacity variable to facilitate estimation in the aggregate treatments.

The specific procedure for generating output is as follows. For each hypothesized week, random draws of inputs are taken from the exogenously provided distribution of inputs and capacities. The appropriate number of random draws are taken from each plant size category to maintain consistency with the structure and plant size distribution in each of the two regions. For each observation, y_{it} is then calculated using the production function (equation 27), with the various parameter values from Table IV imposed according to the technology being simulated.

Generating Output Price

Output price is provided exogenously for each observation. The price is based on a $110.00 per cwt. boxed beef cutout value, but adjusted to reflect the fact that in the models estimated in this experiment the output price is in terms of units of fed cattle procured rather than units of output sold. In addition, the output price is

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[8] ρ_{ij} is the correlation between input I and input j, and σ_i is the standard deviation of input I.

adjusted for each technology to reflect the divergence between the average number of units of regional output produced by the model and the average number of hundredweights of fed cattle that would be expected to be produced in the region based on reported plant capacities. Thus, the price is adjusted to reflect a different scaling interpretation of the output value. After being specified in scaled form, the output price is randomly disturbed by a maximum of 5% from the assigned value for each observation at the disaggregate level. Adding this small amount of variability to the output price adds an element of realism to the experiment in that output price is not constant in the industry.

<u>Generating Input Prices For Each Scenario</u>

This section provides a detailed discussion on how the rest of the variables of each data observation are generated consistent with profit maximizing behavior for each of the 5 behavioral scenarios. For this study, data

$$\text{Max } p = P_t y_{it} - w_{1t}(Y_t) y_{it} - VC(K_i, w_{2t}, w_{3t}, w_{4t}, y_{it})$$

are generated consistent with each plant's solution to the following profit maximization problem:

where:

P_t = Composite price of all of the outputs resulting from the slaughtering and processing of fed cattle in time t;

w_{1t} = Cost per unit (cwt) of procuring live cattle in time t;

w_{2t} = Cost per unit of labor in time t;

w_{3t} = Cost per unit of energy in time t;

w_{4t} = Cost per unit of other processing materials in time t;

K_i = the designed capacity of plant I;

y_{it} = number of units (cwts) of cattle processed by plant (or firm) I in time period t; and

Y_t = Total units of cattle processed in the region in time period t = $(\sum_i y_{it})$.

For scenario's 1, 2, 3, and 5 it is assumed that each plant acts as an individual profit center, making decisions regarding output and input usage on a weekly basis. For these scenarios, the y_{it} in equation (28) represents individual plant production. In scenario 4, it is assumed that each firm acts as a profit center within each region, thus y_{it} from equation (28) represents the firm's production. Because the multi-plant firms control more volume, the potential for exercise of market power is amplified if this assumption holds.

Based on the "primal" approach to data simulation, with the technology imposed by the parameters of the production function, output levels are calculated from the input quantities. The specifics of this step were outlined earlier. After calculating output, a vector of input prices consistent with profit maximizing behavior are calculated from the profit maximization problem to complete the data set for each observation.

Specifically, the first order condition for profit maximization implies that $\dfrac{\partial p}{\partial y_i}$ equals zero. From equation (28):

For the first scenario it is assumed the supply of fed cattle is perfectly elastic, and each plant recognizes

$$\frac{\partial p}{\partial y_i} = P - w_1 * (1 + \frac{\partial w_1}{\partial Y} * \frac{\partial Y}{\partial y_i} * \frac{y_i}{w_1}) - \frac{\partial VC}{\partial y_i} = 0$$

it's lack of ability to influence the cattle price through output changes. In this case, the $\dfrac{\partial w_1}{\partial Y}$ term in equation (29)

$$\frac{\partial p}{\partial y_i} = P - w_1 - \frac{\partial VC}{\partial y_i} = 0$$

is zero and plants behavior is consistent with the simplified first order condition expressed as:

For this behavioral scenario the value of w_1 (the per unit procurement cost of cattle) is provided exogenously. The value provided is based on a $70.00 per cwt. average fed cattle price. However as with output price, it is adjusted for each technology to reflect the divergence between average simulated output and an estimate of actual average output.

As presented in Table I, for scenarios 2, 3, 4, and 5 it is assumed that there is at least some potential for exercise of market power in the fed cattle market. This amounts to assuming that the supply of fed cattle is not perfectly elastic and that the price of fed cattle is related to the quantity of fed cattle sold in the region during the relevant time period (week). An assumed value of the regional fed cattle supply price flexibility ($\frac{\partial w_1}{\partial Y_r} * \frac{Y_r}{w_1}$) is used to determine the value of w_1. By assigning a value to $\partial w_1/\partial Y$ (the slope of the fed cattle supply curve), one can calculate w_1 as [($Y_r * (\partial w_1/\partial Y)) /$ (the price flexibility)]. The price flexibility is provided exogenously, consistent with the range of fed cattle price distortions found by previous researchers (Koontz *et al*., Azzam and Schroeter), and varies in magnitude depending upon the amount of market power potential desired. By varying the assigned value of $\partial w_1/\partial Y$, and the price flexibility, the magnitude of the potential for market power in the input procurement market is changed. The values of w_1 generated are consistent with variation around a $70.00 per cwt. fed cattle market in all cases.

The assumptions regarding the magnitude of the supply price flexibility for the various behavioral scenarios are as follows. For the second scenario, a fed cattle supply price flexibility of between .03 and .04 is imposed on the data. The data are generated such that the supply flexibility increases within this narrow range as regional output increases within the range of it's generated values. Individual plants are assumed to recognize the full market power potential of this supply flexibility. This assumption is consistent with a 10% increase in the quantity of fed cattle demanded by packers resulting in a price increase of from $70.00 per cwt. to $70.25 per cwt. This is thought to be a very small potential for market power, especially at the plant level, and is consistent with previous findings of only slight exercise of market power in fed cattle markets (Koontz *et al.*).

For the third scenario, a fed cattle supply price flexibility of between .15 and .17 is imposed on the data, again increasing within this range as regional output increases. Again, each plant is assumed to recognize the potential of this flexibility. As an example of the price distortion potential of this flexibility, a 10% movement along the supply curve could result in the fed cattle price increasing from $70.00 per cwt. to $71.12 per cwt. This is thought to be a moderate amount of market power potential that should be detectable in any modeling effort to test for market power, and is consistent with the higher end of previous estimates of market power in fed cattle markets (Azzam and Schroeter).

In the fourth scenario, where the firm rather than the plant is assumed to be the decision maker within each region, a fed cattle supply flexibility of .03 to .04 is again imposed on the data, and the firms are assumed to fully recognize this potential for market power. At the regional level, this results in the same potential for fed cattle price changes as in scenario 2. Each multi-plant decision maker, however, influences a larger share of the regional market, thus the $\frac{\partial w_1}{\partial Y}$ term from equation (29) is multiplied by a larger y_i. This increases the potential for price distortion in the fed cattle market by individual decision makers. For scenarios 2, 3, and 4 the decision makers are assumed to behave according to the solution to equation (29).

For scenario 5, the plant is assumed to be the decision maker and, as in scenario 2, a relatively small supply flexibility of .03 to .04 is imposed on the cattle price data. In this scenario, however, the plants do not recognize their ability to influence the fed cattle price and do not account for this ability when making their output decisions. The price of cattle is generated to be dependent upon regional output, but plant behavior is consistent

with the solution to equation (30). Market power should be no more detectable under this scenario than under scenario 1.

To this point, y_1 has been calculated from the production function and w_1 has been exogenously provided or calculated based on regional output and assumed flexibilities. With the assigned value of $\partial w_1/\partial Y$ and the assumption that $\partial Y/\partial y_i$ equals 1, and an exogenously provided P, we can calculate $\dfrac{\partial VC}{\partial y_i}$ (marginal cost) as a residual from equation (29) [or (30) in scenarios 1 and 5].

Profit maximizing behavior is assumed on the part of the individual plants, therefore, the variable cost function in equation (28) represents the variable costs associated with utilizing the cost minimizing bundle of

$$\text{Min} \quad w_2\, x_2 + w_3\, x_3 + w_4\, x_4$$

$$s.t. \quad f(\, x_2, x_3, x_4, k_i\,) - y_i = 0$$

inputs that will produce y_{it}. Solving the first order conditions of the cost minimization problem written as:

results in the following:

$$w_j = \lambda\, \frac{\partial y}{\partial x_J}$$

and from the envelope theorem (Varian, p. 76) it is shown that λ in this problem must be $\dfrac{\partial VC}{\partial y_i}$ (marginal cost).

The term $\dfrac{\partial y}{\partial x_j}$ is simply the marginal product of x_j from the production function. Therefore, we have all of the information necessary to calculate w_2, w_3, and w_4 using equation (32), completing the data requirements.

The Aggregation Levels

In the experiment, tests for market power are first performed using disaggregate data. It is assumed that output, and thus input, decisions are made in this industry on a weekly basis. During a given week, plant- (or firm-) level managers evaluate market conditions and decide how many hours the plants will operate the following week. Procurement plans are formulated accordingly. Therefore, data are generated to represent the collection of 52 weeks of data at the plant or firm-level from the two major U.S. beef packing regions. In the treatments using plant-level data, this represents 52 weeks of data from 18 plants. In the treatments using firm-level data (scenario 4), this represents 52 weeks of data from 7 firms.

The tests for market power are next conducted at the weekly industry aggregate level. These data are obtained by combining the weekly disaggregate data from each plant (or firm in scenario 4) into weekly aggregates.

Twenty years of weekly plant-, or firm-, level data are generated for the third aggregation level. These data are then aggregated over plants, or firms, to yield 20 years of weekly industry aggregates. Then 80 quarterly observations are created by combining each 13week period into one observation. This final data set is representative of 20 years of quarterly industry aggregate data. The aggregation from plant or firm data to regional industry data is similar to aggregation over time, so the results of these types of aggregation on estimates of market power are expected to be similar.

A sufficient number of observations is needed in each data set to allow for ample degrees of freedom in the tests for market power. For this study, the number of observations generated is at least as large as that of previous studies investigating market power problems in meat packing (Schroeter and Azzam 1990, Schroeter 1988, Azzam and Pagoulatos, and Stiegert *et al.*). At the most disaggregate level where the individual plant is assumed to be the decision maker, each data set contains 936 observations, consisting of 52 weeks of weekly data from 18 plants. For the treatments where the firm is assumed to be the decision maker (scenario 4), each disaggregate data set contains 364 observations, consisting of 52 weeks of data from 7 firms. For each scenario, the industry level data sets contain 52 weekly observations, and each quarterly data set contains 80 observations, representing 20 years of quarterly data.

The Models Used To Test For Market Power

The models used to test for market power in this study are econometric systems of equations based on the framework discussed in earlier sections. Each system includes a cost function, input demand or share equations derived from Shephard's lemma for each variable input, and a behavioral equation. The behavioral equation is the plant (or firm) level first order condition for profit maximization. For the systems to be estimated in this study, the

$$P_y \ - \ w_1 \ = \ a_0 * y_i \ - \ \frac{\partial VC}{\partial y_i}$$

general form of the behavioral equation is:

where α_0, the market power parameter, represents $\frac{\partial w_1}{\partial Y} * \frac{\partial Y}{\partial y_i}$.

The goal is to determine if the price of output (marginal revenue) minus the cost of cattle systematically differs from marginal cost. This is accomplished by testing whether or not the market power parameter (α_0) from equation (33) is statistically different from zero. In order to estimate this market power parameter, it is necessary to estimate the marginal cost parameters simultaneously. In the remainder of this section, each of the three econometric systems used to estimate the market power parameter is specified. Each system is based on a different specification of the cost function, allowing a comparison of how the tests for market power are affected by functional form.

The Generalized Leontief System

Consistent with previous studies of market power in the beef packing industry (Schroeter and Azzam

$$VC \ = \ C(\ y_i, K_i, w_2, w_3, w_4)$$

1990, 1991, Schroeter 1988, Stiegert *et al.*), in the first instance, the cost function:

is represented by a generalized Leontief with a fixed input and is therefore assumed to be of the form such that the function is homogeneous by definition, and the only restrictions needed are symmetry.

To increase the efficiency of estimation, factor demands are derived from Shepherd's lemma for inputs x_1 through x_4, which are of the form:

$$x_i = y * (\sum_{j=2} g_{ji} (\frac{w_j}{w_i})^5) + k * (\sum_{j=2} d_{ji} (\frac{w_j}{w_i})^5)$$

$$VC = y*\left(\sum_{i=2}\sum_{j=2}g_{ij}\,w_i^{.5}\,w_j^{.5}\right)+k*\left(\sum_{i=2}\sum_{j=2}d_{ij}\,w_i^{.5}\,w_j^{.5}\right)$$

The first order condition of equation (33) is rearranged after re-specification of the market power term

$$P_y - w_1 = a_0*y + g_{22}*w_2 + 2g_{23}*w_2^{.5}\,w_3^{.5}$$

$$+2g_{24}*w_2^{.5}\,w_4^{.5} + g_{33}*w_3$$

$$+2g_{34}*w_3^{.5}\,w_4^{.5} + g_{44}\,w_4$$

$$\frac{\partial w_1}{\partial Y}*\frac{\partial Y}{\partial y_i}$$, represented by α_0 , yielding the following equation for estimation.

Equations (35), (36), and (37) are estimated simultaneously for each treatment, consisting of 100 randomly generated data sets.

At the disaggregate level, the system of equations is estimated using plant-level (or firm-level in the case of scenario 4) data. For the aggregate treatments the system of equations is estimated using the aggregates created from the original plant or firm-level variables. The estimation is initially accomplished using ITSUR in SAS. The perception of a simultaneity problem can arise, especially in the treatments using industry-level or quarterly data. At the plant-level, under the null hypothesis of no market power, plants do not perceive that they can influence the price of cattle by changing output levels. Therefore, under the null hypothesis w_1 and y_i are not simultaneously determined. Even though the aggregates are constructed by aggregating data resulting from these individual level decisions, an argument can be made that at the aggregate level it is not realistic to assume that the price of cattle and industry output are not simultaneously determined. If these two variables are co-determined in the market, then Y is endogenous in the system along with w_1. This must be allowed for by instrumenting for Y in the estimation process since it enters the system as a right hand side variable.

In order to address this potential problem, for all of the aggregate treatments involved in the experiment, two versions of the model are estimated. The first, as previously pointed out, treats Y as an exogenous variable using ITSUR to estimate the system. The second version treats Y as an endogenous variable. In addition to ITSUR, the system is estimated using IT3SLS in SAS using all exogenous variables in the system, as well as the rank of observation Y_t in the data set relative to all other observations of Y, as instruments.

The Translog System

To represent the second functional form, the cost function in equation (34) is assumed to be translog of the form:

$$\ln(VC) = d_0 + d_y \ln(y) + g_{yy} \ln(y)^2 + \sum_{i=2}^{4} d_i \ln(w_i)$$

$$+ \sum_{i=2}^{4} g_{iy} \ln(w_i) \ln(y) + .5 \sum_{i=2}^{4} \sum_{j=2}^{4} g_{ij} \ln(w_i) \ln(w_j) + d_k \ln(k)$$

$$+ g_{kk} \ln(k)^2 + \sum_{i=2}^{4} g_{ik} \ln(k) \ln(w_i) + g_{yk} \ln(k) \ln(y)$$

Homogeneity is imposed by the following restrictions: $\sum_i d_i = 1$, $\sum_i g_{iy} = 0$,

$\sum_i g_{ij} = 0$ for all j, and $\sum_j g_{ij} = 0$ for all I. Symmetry is imposed by restricting γ_{ij} to be equal to γ_{ji} in all cases.

Again, in order to increase the efficiency of the parameter estimates, the system is supplemented by 2 of the 3 variable cost share equations stemming from Shepherd's lemma . Specifically, the two additional equations to be added to the system are:

$$\frac{x_2 * w_2}{VC} = d_2 + g_{2y} \ln(y) + g_{22} \ln(w_2)$$

$$+ g_{23} \ln(w_3) + (-g_{22} - g_{23}) \ln(w_4) + g_{2k} \ln(k)$$

$$\frac{x_3 * w_3}{VC} = d_3 + g_{3y} \ln(y) + g_{23} \ln(w_2)$$

$$+ g_{33} \ln(w_3) + (-g_{23} - g_{33}) \ln(w_4) + g_{3k} \ln(k)$$

and:

The first order condition of equation (33) is rearranged, after specification of the market power term as before, and allowing for the fact that $\dfrac{\partial VC}{\partial y_i} = \dfrac{\partial \ln(VC)}{\partial \ln(y_i)} * \dfrac{VC}{y_i}$, to yield the following:

In this form, the equation would be difficult to estimate in the system because the VC term is an endogenous

$$P_y - w_1 = a_0 * y_i + \frac{\partial \ln(VC)}{\partial \ln(y_i)} * \frac{VC}{y_i}$$

variable to the system and would thus have to be specified as the antilog of equation (36) nested within equation

(39). This problem is addressed by subtracting $\alpha_0 * y_i$ from both sides, dividing both sides of equation (39) by VC,

$$COST = \cfrac{(P_y - w_1 - a_0 * y)}{\cfrac{d_y + 2g_{yy} * \ln(y) + g_{2y} * (\ln(w_2) - \ln(w_4)) + g_{3y} * (\ln(w_3) - \ln(w_4)) + g_{ky} * \ln(k)}{y}}$$

then dividing by $(P_y - w_1 - \alpha_0 * y_i)$ and inverting to yield the following equation for estimation:

Again, the system consisting of equations (38), (39), (40), and (42) is estimated simultaneously using ITSUR for the disaggregate treatments, and both ITSUR and IT3SLS for all aggregate treatments.

The Quadratic System

The final functional form for the specification of equation (34) to be investigated in this study is a quadratic specification. Normalizing all input prices and cost by w_4 imposes homogeneity and results in the following specification for estimation:

$$COST_n = d_0 + d_y * y + g_{yy} * y^2 + d_2 * w_{2n} + d_3 * w_{3n}$$

$$+ g_{22} * w_{2n}^2 + g_{23} * w_{2n} * w_{3n} + g_{33} * w_{3n}^2 + g_{2y} * w_{2n} * y + d_{3y} * w_{3n} * y$$

$$+ d_k * k + g_{kk} * k^2 + g_{2k} * w_{2n} * k + g_{3k} * w_{3n} * k + g_{ky} * k * y$$

Where $COST_n = (COST/w_4)$, $w_{2n} = (w_2/w_4)$, and $w_{3n} = (w_3/w_4)$.

As with the other functional forms, the cost function is supplemented with factor demand equations to

$$x_2 = d_2 + g_{2y} * y + 2g_{22} * w_{2n} + d_{23} * w_{3n} + g_{2k} * k$$

increase the efficiency of the cost function parameter estimates as follows:

$$x_3 = d_3 + g_{3y} * y + 2g_{33} * w_{3n} + d_{23} * w_{2n} + g_{3k} * k$$

and,

Finally, the first order condition of equation (33) with the market power term specified as before, is written as follows for estimation:

$$P_y - w_1 = a_0 * y + d_y * w_4 + 2g_{yy} * w_4 * y$$

$$+ g_{2y} * w_4 * w_{2n} + g_{3y} * w_4 * w_{3n} + g_{ky} * w_4 * k$$

This system, consisting of equations (43) through (46), is estimated simultaneously. Again, both ITSUR and IT3SLS are used for all aggregate treatments.

Each econometric system is estimated separately for each data set generated. With the data sets generated at different levels of aggregation, results of the tests for market power can be compared across aggregation levels to determine the effect of aggregation on the tests for market power. The results of estimating these econometric systems using each of the generated data sets are summarized and discussed in the next section.

Summary

Detail on the simulation process has been provided in this section. The reader with some familiarity with the data and related analytical procedures may be interested in this detail. The reader with less analytical background, but interested in what this means for the industry, will need to keep the primary message in mind: The simulation is designed to determine whether the widely used and still developing NEIO methodology, as described in earlier sections and in the studies referenced, is capable of accurately spotting market power when the only data available are public data which have been aggregated over time or across firms. The simulations also test whether the choice of functional form in estimating the cost curves and profit maximization equation makes a difference. If the aggregation and/or choice of functional form negates or sharply reduces the effectiveness of the tests for market power, then the work now available in the research literature may be inadequate or even misleading as a base for the administering of antitrust legislation in the beef packing sector. Obviously, this is an important issue and merits time and attention to detail.

RESULTS

The results of the Monte Carlo experiment are presented in this chapter. The experiment examines the effectiveness and accuracy of statistical tests of a null hypothesis of no market power at various levels of data aggregation. To make the experiment as useful as possible, a few reminders are useful here. The experiment is repeated for each of 13 technologies and 5 assumptions regarding firm behavior for each aggregation level. The technologies differ by ease of substitution between factors and returns to scale. The behavioral scenarios differ by the potential for, and exercise of, market power by the decision makers in the industry. For each technology/behavior combination, 3 distinct data sets are created that reflect 3 different aggregation levels. The first aggregation level represents weekly data collected from individual plants (or firms in scenario 4). The second aggregation level represents industry-level data (aggregated across plants or firms) collected on a weekly basis. The third aggregation level represents industry-level data collected at weekly intervals and aggregated to quarterly time intervals. For each technology-behavioral scenario-aggregation level treatment, 100 unique data sets are generated for the experiment.

When weekly plant- or firm-level data are not aggregated, the econometric models specified to test for market power are estimated using Iterative Seemingly Unrelated Regression (ITSUR). Each data set is tested using 3 alternative specifications, which differ by functional form, and functional form may impact on the tests. The 3 functional forms compared in this experiment are the generalized Leontief, the translog, and the normalized quadratic.

When the data are aggregated (either over firms, or over both firms and time), each specification of the model used to test for market power is estimated using 2 alternative methods, ITSUR and Iterative Three Stage Least Squares (IT3SLS). The second estimation method accounts for the possibility that procurement levels (output) and fed cattle prices may be simultaneously determined. The hypothesis of no market power is tested in every aggregate data set using each of the 3 alternative specifications of the market power model, each estimated using the 2 alternative statistical estimation methods.

The results for the 5 behavioral scenarios are summarized in 5 separate tables. Entries down the left hand column of each table indicate which technology (Tech) is being represented by that particular row in the table. Each table is divided into two sections: the first reporting the results of the models estimated using ITSUR, and the second reporting the results of the models estimated using IT3SLS.   For each estimation method, the results are subdivided by the aggregation level of the data generated and tested, and for each aggregation level the results are again subdivided by the functional form assumed to represent the cost function in the market power estimation model.

The individual entries in each result table for every technology-functional form-aggregation level combination reveal the number of times out of 100 that the null hypothesis of no market power is rejected at the 95 percent confidence level using a one tail test (a test of the α_0 parameter from each model).   Following each table representing a particular scenario, the results are discussed and summarized.

Scenario 1 Results

Table V presents the results of scenario 1 in which the fed cattle market supply curve is generated to be perfectly elastic in the relevant time frame. Therefore, plants have no opportunity to exercise market power. One would expect each entry in the table to be approximately 5 percent because the test is set at a .05 significance level.

In interpreting Table V, the reader should remember:

> Each technology, aggregation level, and estimation technique was replicated 100 times. The rejection level of the test statistic used is 5 percent. Technologies 1 through 4 are homogeneous CES, and substitution possibilities for inputs become increasingly difficult moving from 1 to 4. For technologies 5, 6, and 7, the elasticity of substitution is not one value for all pairs of inputs, but rather is one value for three input pairs and another value for the remaining three input pairs. In general, the substitution possibilities become more difficult as one moves from technology 5 to technology 7. Technology 5 reveals slight increasing returns to scale and 6 and 7 reveal slight decreasing returns to scale. Technologies 8 and 9 exhibit a unique elasticity of substitution for each input pair. Technology 8 displays slight decreasing returns to scale and 9 displays slight increasing returns to scale. Technology

10 assumes that capital, energy, and materials are complements to each other, but are all substitutes for labor, and displays slight decreasing returns to scale. Technology 11 is non-homogeneous CES with increasing returns to scale. Technologies 12 and 13 are non-homogeneous with increasing returns to scale, and exhibit a unique elasticity of substitution for each input pair.

Disaggregate-level data represents weekly observations from 18 individual plants in 2 regions.

Industry-level data represents weekly observations of data aggregated across all 18 plants.

Quarterly data represents quarterly (13 week period) observations of data aggregated across all 18 plants (Industry-level data).

A generalized Leontief functional form was used to represent the cost function in the market power estimation model.

A translog functional form was used to represent the cost function in the market power estimation model.

A normalized quadratic functional form was used to represent the cost function in the market power estimation model.

Table V. Percent Rejection of the Null Hypothesis of No Market Power When No Market Power is Present.[a]

| | ITSUR | | | | | | | | | IT3SLS | | | | | |
| | Disaggregate | | | Industry Level | | | Quarterly | | | Industry Level | | | Quarterly | | |
Tech.	GL	TL	Q	GL	TL	Q	GL	TL	Q	GL	TL	Q	GL	TL	Q
1	80	11	84	24	22	7	1	11	4	11	23	8	1	12	4
2	28	14	0	16	23	12	1	13	3	17	30	10	1	11	3
3	0	18	0	12	20	17	2	4	0	13	20	10	2	6	3
4	0	8	18	1	12	7	3	2	0	3	12	5	3	3	11
5	0	16	0	27	16	2	0	6	5	17	16	2	0	8	7
6	98	100	100	100	0	8	100	3	100	100	0	5	100	0	100
7	100	100	100	94	17	100	100	68	100	86	10	96	100	10	100
8	89	6	1	14	17	14	79	1	0	14	15	12	89	4	0
9	68	2	0	97	20	2	0	10	13	97	21	2	0	12	23
10	100	6	100	100	91	100	100	47	100	100	91	100	100	36	100
11	68	6	0	14	34	8	100	30	18	14	35	6	100	31	17
12	100	8	98	100	86	100	100	100	100	100	87	100	100	100	96
13	89	20	75	8	85	19	100	98	70	9	85	18	100	98	72

The results reported in Table V indicate that even using disaggregate-level data (considered to be the most ideal data), there is a significant danger of rejecting the hypothesis of no market power, which says market power is present, when market power is in fact not present. For many of the functional form/technology combinations, the actual size of the test is significantly different from the nominal size of the test (.05) because the models tend to reject the null hypothesis of no market power too often. However, when using disaggregate data, all models tend to have high total explanatory power. The R^2 statistic was high, .95 and larger, when the first replication of each data set was tested. The translog specification performs by far the best across the full range of technologies examined. Only for technologies 6 and 7 (slight decreasing returns to scale, and fairly low elasticities of substitution between inputs) did the translog perform poorly. The translog is not expected to perform as well for technologies that exhibit very low elasticities of substitution because when the higher order terms are excluded, the translog becomes a Cobb Douglas with an elasticity of substitution of 1 for each input pair. The translog did perform quite well for some technologies that exhibit fairly low elasticities of input substitution (3, 4, and 8). The quadratic and the generalized Leontief systems yield similar results when testing disaggregate data. Both of these models are expected to perform well when the elasticities of input substitution are fairly low because when the higher order terms are excluded from the quadratic it is very similar to Leontief, which represents a technology with no input substitution possibilities. With the exception of technology 7, this expectation is fulfilled when testing the scenario 1 disaggregate data. Because of the included higher order terms, the quadratic system is expected to, and does, perform somewhat better than the generalized Leontief for some of the technologies with greater substitution possibilities between inputs (2, 8, and 9).

Prior expectations regarding the effects of data aggregation depend on the underlying technology. The first four technologies are homogeneous (exhibit constant returns to scale). Aggregation should not affect the results of tests for market power in these treatments because aggregation is possible for homogeneous technology. Technologies 5 through 10 deviate slightly from constant returns to scale. It is expected that aggregation will affect the results of the test for market power for these technologies. The last three technologies exhibit significant increasing returns to scale. Data aggregation is again expected to affect the results of the test for market power.

When using weekly industry-level aggregate data, all models tend to have very high explanatory power with R^2 .90 and larger. However, the simulation results change significantly. When using the ITSUR method to estimate the translog model, the number of false rejections remains fairly constant when using the industry aggregate data instead of the disaggregate data to test the first four technologies. In contrast, the number of false rejections increases when testing industry aggregate data generated via technologies 5 through 10. Exceptions include technologies 6 and 7, where the translog did not perform well in the disaggregate treatments. As expected, the number of false rejections increases significantly when using the translog to test industry aggregate data from the last 3 technologies, which exhibit increasing returns to scale. The expected changes in results do not appear when using either the generalized Leontief or the quadratic to test industry-level data. Since the expectations are fulfilled when using the translog, which is the most flexible of the functional forms compared, the erratic and unexpected results from the other two specifications are attributed to inappropriate functional form specification. The results obtained from the two different estimation methods are virtually identical for all models, and the same general inferences can be garnered from the results of the models using IT3SLS as from those using ITSUR.

When using the industry quarterly data to estimate the models, results again change significantly in terms of the number of false rejections. Differences between the two estimation methods are virtually nonexistent. The overall explanatory power of the models decreases significantly with R^2 now as low as .50 for the first replication. For the translog model, the results remain somewhat consistent with results obtained using the weekly industry-level data, though the number of rejections decreases somewhat for a few of the technologies. This decrease in the number of rejections for some technologies can be attributed to an increase in the variance of all parameter estimates, including the market power parameter, when using the highly aggregated data. For the first 10 technologies, which all exhibit nearly constant returns to scale, both the generalized Leontief and the quadratic models fail to reject the hypothesis of no market power the most often when applied to the quarterly industry-level data. This result is also primarily attributed to the increased parameter variance when using the quarterly aggregate data. At first impression, this could draw one to the conclusion that highly aggregated data are well suited for this empirical technique. This would be a premature and misleading conclusion. First, note that when testing the technologies that exhibit significant increasing returns to scale (11,12, and 13) the number of false rejections tends to increase when testing the aggregate quarterly data relative to the number of rejections when testing disaggregate or weekly industry data. Second, for several of the technologies generated and tested in the experiments described below where plants (or firms) do in fact exercise market power, the existence of market power is often not detected in the aggregate data treatments but is correctly detected in the disaggregate treatments.

Scenario 2 Results

        Table VI presents the results of using the models to test for market power in scenario 2. In this scenario, some market power is exercised because a very small (.03 to .04) non-zero price flexibility is imposed on each regional fed cattle supply curve, and each plant is assumed to take this fact into consideration when making it's profit maximizing procurement, and thus output, decisions. One would expect more rejections of the null hypothesis of no market power for each treatment in this scenario than in scenario 1, because the null hypothesis of no market power is not really true. The table is structured the same as Table V above.

        When using the disaggregated data, Table VI reveals that all models are able to detect even the very small amount of market power being exercised by industry participants, indicating that the power of the test is very high. These results are somewhat surprising. *A priori*, it was assumed that this small amount of market power would result in only a few more rejections of the null hypothesis of no market power than in scenario 1 because the amount of market power being exercised is in fact very small.

Table VI. Percent Rejection of the Null Hypothesis of No Market Power When a Small Amount of Market Power is Present.

| | ITSUR | | | | | | | | | IT3SLS | | | | | |
| | Disaggregate | | | Industry Level | | | Quarterly | | | Industry Level | | | Quarterly | | |
Tech.	GL	TL	Q	GL	TL	Q	GL	TL	Q	GL	TL	Q	GL	TL	Q
1	100	100	100	100	100	100	0	67	0	100	100	100	0	60	0
2	100	100	100	100	100	100	100	61	100	100	100	100	100	55	100
3	100	100	100	100	100	100	100	61	100	100	100	100	100	54	100
4	100	99	100	100	100	100	100	59	100	100	100	100	100	49	100
5	100	100	100	100	100	100	0	0	0	100	100	100	0	0	0
6	100	100	100	100	0	2	100	4	100	100	0	0	100	12	100
7	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
8	100	100	100	100	100	100	100	100	100	100	100	100	100	98	100
9	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
10	100	100	100	100	19	88	100	100	100	100	16	92	100	91	100
11	100	100	100	100	100	100	0	100	0	100	100	100	0	100	0
12	100	100	100	100	100	100	100	98	100	100	100	100	100	96	100
13	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

Similarly, when the ITSUR models are estimated using the <u>weekly</u> industry aggregated data, the null hypothesis is rejected nearly 100% of the time for each technology and model specification. The notable exceptions include technology 6 when using both the translog and the quadratic model specifications, and technology 10, primarily when using the translog model. Only slight differences in results are observed between the two estimation methods.

When using the <u>quarterly</u> industry aggregated data to test for market power, the null hypothesis is less likely to be rejected. Using either estimation method, both the generalized Leontief and the quadratic models tend to either reject none of the time or reject all of the time, depending on the underlying technology. The technologies which yield no rejections are the same using both the generalized Leontief and the quadratic models. This result is not surprising since these two models are expected to perform similarly for the same technologies. The translog model does not yield these "always or never" results when testing the quarterly aggregate data. The model does, however, fail to reject the null hypothesis of no market power a number of times for each of the first six technologies. This result is again attributed to the increased parameter variance when using quarterly aggregated data. The null hypothesis is rejected slightly less often when using IT3SLS to estimate the translog model. These results differ markedly from those obtained using the same model to test either disaggregated data or aggregated industry-level but weekly data.

Scenario 3 Results

Table VII presents the results of the tests for market power in scenario 3. For this scenario a significant amount of market power is exercised because a moderate (.15 to .17) non-zero price flexibility is imposed on each regional fed cattle supply curve, and the behavior of each plant is simulated such that this market power potential is accounted for in each profit maximizing output decision. It is expected that the null hypothesis of no market power will be rejected virtually all of the time for each treatment, because of the significant exercise of market power. Again, the table is structured in the same way.

Table VII reveals that there is little chance that any of the models specified for this experiment would fail to discover the moderate exercise of market power in the disaggregated data. As in scenario 2, the power of the test is apparently quite high because, for every production technology, the existence of market power is revealed 100 percent of the time using each of the three model specifications.

Also, when testing for market power using data generated at the weekly aggregate industry-level, both the ITSUR models and the IT3SLS models reveal the market power the vast majority of the time. The only exceptions are found when analyzing technology 6 data, where both the translog and the quadratic models do not reveal the market power all of the time, and when analyzing the complementary input data (technology 10), where the translog and the quadratic models reveal the market power most, but not all, of the time.

Table VII.   Percent Rejection of the Null Hypothesis of No Market Power When a Moderate Amount of Market Power is Present.

	ITSUR									IT3SLS					
	Disaggregate			Industry Level			Quarterly			Industry Level			Quarterly		
Tech.	GL	TL	Q	GL	TL	Q	GL	TL	Q	GL	TL	Q	GL	TL	Q
1	100	100	100	100	100	100	1	100	0	100	100	100	2	100	0
2	100	100	100	100	100	100	100	100	100	100	100	100	100	93	100
3	100	100	100	100	100	100	100	100	100	100	100	100	100	95	100
4	100	100	100	100	100	100	100	100	100	100	100	100	100	95	100
5	100	100	100	100	100	100	0	68	0	100	100	100	0	64	0
6	100	100	100	100	39	80	100	93	100	100	37	79	100	80	100
7	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
8	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
9	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
10	100	100	100	100	92	97	100	100	100	100	91	97	100	96	100
11	100	100	100	100	100	100	0	100	0	100	100	100	0	100	0
12	100	100	100	100	100	100	100	100	100	100	99	100	100	98	100
13	100	100	100	98	100	100	100	100	100	98	100	100	100	100	100

Once again, when the data are aggregated to the quarterly level, the results change. As was the case when testing the scenario 2 quarterly data, both the generalized Leontief and the quadratic models tend to reveal the market power either all of the time, or virtually none of the time, and as expected these two models again tend to perform in very similar fashion across the technology spectrum. The translog model reveals the market power the majority of the time for all technologies, but fails to reveal the market power in several of the replications of technology 5, and a few of the replications of technology 6. When using the IT3SLS method to estimate the translog model, the null hypothesis of no market power is slightly less likely to be rejected across the technology spectrum than when using ITSUR.

Scenario 4 Results

The results of the tests for market power in scenario 4 are presented in Table VIII. As in scenario 2, a small amount of market power is present because the same very small (.03 to .04), but non-zero, price flexibility is imposed on the fed cattle supply curve, and the decision makers recognize this potential for market power. In this instance, however, it is the firm, rather than the plant, that is the decision maker. Therefore, unlike in the previous three scenarios, the dissaggregate-level data represents weekly observations from individual firms in two regions. This increases the share of the total procurement market that is controlled by some decision makers and, for a given supply flexibility, increases the potential for exercise of market power by those decision makers. One would expect more rejections of the hypothesis of no market power for each treatment in this scenario than in scenario 2 because of this increased potential for market power.

Using disaggregated data, the results in Table VIII indicate that the power of the test is quite high and that all of the models reveal the exercise of market power 100 percent of the time for all technologies. One would expect the exercise of market power to be even easier to detect in this scenario than in scenario 2, since some decision makers control a larger share of the market. Based on a comparison of the results reported in Tables VI and VIII this expectation is not easy to discern because the market power is revealed essentially all of the time in both scenarios when using disaggregate level data.

Using weekly industry-level aggregated data, all of the ITSUR models again detect the market power the vast majority of the time for most of the technologies. The exceptions occur with technologies 6 and 10, and as was the case in scenario 2, it is the translog model which reveals results for these technologies that are inconsistent with the results of testing the rest of the technologies. Results from the two estimation methods are very similar for this scenario-aggregation level combination.

Results change dramatically when the ITSUR models are used to test the quarterly aggregated data in this scenario. As was the case for previous scenarios, results from both the generalized Leontief and the quadratic models are erratic. Depending on the technology, the null hypothesis of no market power tends to be either rejected almost always or almost never, and as expected, these two models perform similarly across the technology spectrum. Clearly, the generalized Leontief and quadratic models do not consistently reveal the market power when using the highly aggregated quarterly data, especially when the underlying technology exhibits nearly constant returns to scale. Supplemental results in parentheses for selected

Table VIII. Percent Rejection of the Null Hypothesis of No Market Power When the Firm, Rather Than the Plant, is the Decision Maker and a Small Amount Market Power is Present.

| | ITSUR | | | | | | | | | IT3SLS | | | | | |
| | Disaggregate | | | Industry Level | | | Quarterly | | | Industry Level | | | Quarterly | | |
Tech.	GL	TL	Q	GL	TL	Q	GL	TL	Q	GL	TL	Q	GL	TL	Q
1	100	100	100	100	100	100	0	27	0	100	100	100	0	25	0
2	100	100	100	100	100	100	0 (4)	100	0	100	100	100	0 (4)	100	0
3	100	100	100	100	100	100	5 (31)	100	4 (32)	100	100	100	8 (35)	100	22 (59)
4	100	100	100	100	100	100	99	100	100	100	100	100	99	99	100
5	100	100	100	100	98	100	0	8	0	100	97	100	0	12	0
6	100	100	100	100	0	100	100	99	100	100	3	100	100	99	100
7	100	100	100	100	90	94	100	100	100	100	94	90	100	100	100
8	100	100	100	100	100	100	51	100	0	100	100	100	91	100	1 (13)
9	100	100	100	100	100	100	0	100	0	100	100	100	0	100	0
10	100	100	100	100	2	100	16 (68)	100	0 (93)	100	9	100	17 (73)	37	0 (92)
11	100	100	100	100	100	100	1	100	1	100	100	100	1	100	1
12	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
13	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

entries indicate the number of rejections at the 10 percent level using a one tail test. They are included to reveal that in many instances the results are on the borderline between reject and fail to reject using the 5 percent level test statistic. The translog specification more consistently reveals the exercise of market power in the aggregate data across the technology spectrum, and the results are more consistent with the findings at lower levels of data aggregation.   More so than in the previous scenarios, some differences do show up between the two estimation methods when testing the quarterly aggregate data. For some model specification-technology combinations, the IT3SLS models are slightly more likely to reject the null hypothesis than the ITSUR models, though the differences are usually not large.

Scenario 5 Results

 Table IX presents the results of testing for market power in scenario 5. This is the scenario in which a small (.03 to .04) non-zero price flexibility is imposed on the regional fed cattle supply relationships, but the individual plants do not recognize this potential to exercise market power. In making their individual profit maximization decisions, the plants behave as if they faced a horizontal fed cattle supply curve, and therefore do not actually exercise any market power. This scenario is included to determine if the models are detecting actual decision maker behavior with regard to market power, or simply potential for market power. If the models are detecting actual behavior, one would not expect the tests to reveal the exercise of market power. Ideally, the entries in this table should all be approximately 5 percent, consistent with the nominal size of the test. Realistically (considering the previous results) it is hoped that the results will be similar to those of scenario 1.

 The results of testing for market power in scenario 5 using the disaggregate data are indeed similar to those of scenario 1. The large number of entries in Table IX greater than 5 indicate that once again the actual size of the test is much larger than the .05 nominal size of the test for many of the functional form/technology combinations. The generalized Leontief performs the poorest, falsely rejecting the hypothesis of no market power a large portion of the time, but does not perform much worse in this scenario than in scenario 1. Both the generalized Leontief and the quadratic specifications tend to correctly identify the absence of market power when testing technologies that exhibit fairly low elasticities of substitution between input pairs. As expected, however, both the generalized Leontief and the quadratic specifications perform poorly for most of the technologies that allow for significant substitution possibilities between input pairs. As in scenario 1, the translog specification correctly leads to a conclusion of no market power more consistently than the other two models. The only significant exception occurs when testing the technology 6 data, which exhibits fairly low elasticities of substitution between inputs.   Depending on the technology, the translog model either falsely rejects the null hypothesis a few more times, or a few less times, than it did in scenario 1, however the results are quite consistent with those of scenario 1. The numbers in parentheses for selected entries indicate the number of times that the null is rejected at the 1% level, and reveal that in several instances the null hypothesis is just barely rejected at the 5% level.

Table IX. Percent Rejection of the Null Hypothesis of No Market Power When a Small Amount of Market Power is Possible, but Not Recognized by the Plants.

| | ITSUR | | | | | | | | | IT3SLS | | | | | |
| | Disaggregate | | | Industry Level | | | Quarterly | | | Industry Level | | | Quarterly | | |
Tech.	GL	TL	Q	GL	TL	Q	GL	TL	Q	GL	TL	Q	GL	TL	Q
1	82 (61)	23 (10)	73	7	35 (17)	7	1	11	4	5	35 (17)	7	1	12	4
2	12	25 (9)	0	35	54	20 (6)	100	100	100	33	44	22 (8)	100	93	100
3	20 (11)	47 (33)	0	41	65 (43)	8	100	100	100	40	59	10	100	95	100
4	0	30	18	28	47	10	100	100	100	27	41	8	100	94	100
5	19	10	1	19	12	2	0	0	0	17	12	3	0	0	0
6	100	100	100	99	0	0	100	93	100	99	0	0	100	87	100
7	100	35	100	87	5	10	100	100	100	86	4	7	100	100	100
8	97	13	0	38	25	1	100	100	100	40	28	1	100	100	100
9	67	1	0	42	2	12	100	100	100	41	3	12	100	100	100
10	100	4	100	100	84	100	100	100	100	100	84	92	100	100	100
11	73	13	0	19	60	35	100	48	22	19	52	35	100	45	21
12	99	20	95	90	88	100	100	98	100	83	90	100	100	98	100
13	93	24	78	20	84	31	100	84	82	22	84	30	100	74	84

When using the ITSUR translog model to test weekly aggregated industry data generated via the first four technologies, the number of false rejections remains fairly consistent with the number revealed using disaggregate data. This result is as expected, since these technologies are homogeneous. In general, the number of false rejections increases when using the translog model to test for market power in industry aggregate data when the underlying technology does not exhibit constant returns to scale. This observation is especially true for the technologies exhibiting significant increasing returns to scale (11,12, and 13). In contrast, when using both the generalized Leontief and the quadratic models to test weekly industry-level data, the overall number of false rejections tends to decrease, though this general pattern does not hold for every technology analyzed. Once again, since the most flexible model specification (the translog) performs as expected in most cases, the erratic and unexpected results of the other two models can be attributed to inappropriate model specification in terms of the functional form of the cost function. Differences in results between estimation methods are minor for all models.

Unlike scenario 1, when analyzing the quarterly aggregate data for scenario 5, the number of false rejections tends to increase above the number found at the more disaggregate levels. With the exception of three of the technologies (1, 5, and 11), all ITSUR models reject the hypothesis of no market power nearly all of the time. This result is compatible with expectations, but it is particularly interesting in that it is only in scenario 5 that the number of rejections somewhat consistently increases across the technology spectrum when testing the quarterly aggregate data. Comparisons between the two estimation methods reveal very similar results when analyzing the quarterly data, though the translog model fails to reject the null hypothesis of no market power a few more times for some technologies when estimated using IT3SLS.

Summary

The implications of using data that have been combined across firms into weekly aggregates to test for market power depend on the underlying technology and behavior of the industry being studied. *If the individual decision makers in the industry are not exercising market power, the results of tests for market power change dramatically across aggregation levels.* When using the model specification that does the best job of capturing the true underlying technology and behavior in the disaggregate data sets (the translog functional form), the number of false rejections of the no market power hypothesis tends to increase when industry aggregate data are used for the analysis. As expected, this observation is especially true when the underlying technology exhibits increasing returns to scale. When using the other model specifications, the results are so erratic that consistent conclusions are hard to draw. This evidence suggests that the alternative model specifications (the generalized Leontief and the quadratic) are not flexible enough to capture the true underlying technology.

When the decision makers in the industry are actually exercising market power, all three models used in this study tend to reveal this fact the vast majority of the time in both the disaggregate and weekly industry aggregate data. This is not very encouraging in light of the fact that the underlying behavior is not known and it is this behavior that the analyst is attempting to ascertain. *Given that there is an increased danger of false inference regarding market power when industry participants are behaving competitively when using the industry aggregate data, it appears that a significant information loss results from aggregation over plants or firms.*

When the weekly industry data are aggregated over time to quarterly data, the number of rejections tends to decrease for scenarios 2, 3, and 4 where market power is actually being exercised. In these scenarios, there is an increased danger of not discovering the existence of actual market power when using the quarterly data. For scenario 1, there is an increased tendency to correctly infer no market power when using quarterly data if the true underlying technology exhibits nearly constant returns to scale, but there is an increased danger of falsely inferring the existence of market power if the true underlying technology exhibits increasing returns to scale. In addition, when testing the scenario 5 data sets where market power is possible but not actually being exercised, there is a general tendency for the models to falsely infer market power more often when using quarterly aggregate data across all of the technology scenarios.

The results vary significantly across model specifications for all scenarios. This is an indication that it is critical to accurately capture the underlying technology in the cost function parameters, because any error in capturing the exact technology can be at least partially incorrectly attributed to market power. *Since the true underlying technology is never known, it is imperative that an adequately flexible functional form be used to capture the underlying technology when testing for market power behavior using econometric techniques. Of the*

three functional forms compared in this study, the translog model performs as expected most consistently across the range of technologies, behavioral scenarios, and aggregation levels investigated in this experiment. This is not surprising because the translog is the most flexible of the three functional forms used. What is somewhat surprising is the magnitude of the differences in results between the three models in several of the scenario/aggregation-level combinations.

The true underlying production technology of the industry being studied plays an important role in dictating the success of the efforts to test for market power. Features of certain technologies appear to make them very difficult to model in studies attempting to simultaneously detect the exercise of market power and capture the correct cost function parameters. This is somewhat discouraging as well, given that the true underlying technology is never known.

The results obtained from the ITSUR and IT3SLS estimation methods are virtually identical, so the same general inferences can be garnered from the results of the models estimated using either method. In the context of this experiment, this observation is not surprising because output and cattle prices are not simultaneously determined in the data sets used for this analysis. The comparison does reveal that the IT3SLS procedure could be an appropriate alternative when testing data in which simultaneity is suspected, because even if simultaneity is not present, the IT3SLS procedure performs just as well as ITSUR.

The most striking observation from the results reported in this section is that when testing disaggregated data, there is more danger of "finding" market power when it is not present than not finding it when it is present. This indicates that the actual size of the test for market power is larger than the nominal size of the test, but that the power of the test is quite high. *If a carefully specified model using firm-level data fails to reveal market power, then the researcher, and in turn policy makers and regulatory authorities, can be fairly confident that the industry participants are behaving competitively. On the other hand, if the analysis reveals the presence of market power, the researcher should be careful in placing a high level of confidence in the findings.* Whether market power is actually being exercised or not, the use of highly aggregated data to test for market power tends to significantly bias the results, especially if the underlying technology does not exhibit constant returns to scale. *This finding with regard to aggregated data, especially data aggregated over time, raises questions about the validity of the results of a number of the studies reviewed in the literature review section.* In addition, many of the existing studies use a Leontief-type cost curve specification, and the sensitivity of the results to the choice of fundamental form adds more reason to be concerned about many of the existing studies. It would appear that more emphasis needs to be placed on weekly observations if that is, in fact, the decision period for beef packing plants or firms. And it may be the case that weekly data aggregated across plants (or firms) to protect confidentiality of plant- or firm-level data will prove adequate. Aggregating over time created far more problems than aggregating weekly data across plants or firms.

CONCLUSIONS

In the empirical portion of this study, data consistent with various behavioral assumptions in the U. S. beef packing industry were simulated and tested to see if these data revealed the exercise of market power in the industry. The primary objectives were to determine whether or not estimates of market power remain consistent when the data used to obtain the estimates are aggregated across firms and over time, and to determine the sensitivity of these estimates to model specification.

Three market power models were specified for a Monte Carlo experiment, models that differed in terms of the functional form used to represent the cost function and to capture the underlying technology of the industry being tested. The data generation process was based on a primal approach where input quantities and output price were provided exogenously, output quantities were calculated from the pre-specified production function, and input prices were generated consistent with plant or firm-level profit maximizing behavior. The assumed underlying technology of the beef packing industry was varied across a range of possibilities by altering the production function parameters. The presumed behavior of the decision makers in the industry was altered in the data generation process by imposing different assumptions regarding the potential for, and recognition of the potential for, market power on the part of the individual plants or firms in the industry. For each technology/behavior combination the data sets were generated at three levels of aggregation including weekly firm-level, weekly

industry-level, and quarterly industry-level.

Using Monte Carlo techniques, 100 data sets were generated for each behavior - technology - aggregation level combination (treatment). Each data set was tested using the three different specifications of the market power model to see if the hypothesis of no market power would be rejected. The results of these tests for market power were presented in detail and discussed in earlier sections.

General Conclusions

The effectiveness and usefulness of econometric behavioral models designed to detect and forecast the exercise of market power is based on their ability to do so accurately. These models are derived from well known economic theories of profit maximizing behavior on the part of decision makers in an oligopoly or oligopsony setting. Therefore, if the models are applied to the appropriate data, and are specified in such a way that they capture the underlying technology and behavior of the industry participants, they should yield an unbiased indication of any non-competitive behavior.

The results reveal that, in reality, there is a strong tendency for these behavioral models to generate inaccurate information regarding the exercise of market power. Furthermore, the actual size or significance level of the test for market power is much larger than the nominal size chosen for the test. *There is a significant danger that the models will indicate that market power is being exercised in an industry where in reality it is not.* This danger seems especially true when analyzing data at the disaggregate and weekly industry aggregate levels. *Conversely, the power of the test for market power in general appears to be quite high. There is little danger that the models will fail to reveal the market power when it is actually being exercised.* When using econometric behavioral models to simultaneously estimate market power parameters and technology parameters, it appears that any inability to capture the true underlying technology of the industry is at least partially picked up by the market power parameters. This appears to occur in much the same way that an intercept term would capture systematic deviations not captured by the explanatory terms in a standard linear regression model.

When the data used to test for market power are aggregated to the quarterly industry-level, the explanatory power of the models decreases significantly. The variance of all parameter estimates increases to the point that many parameters become insignificant a large portion of the time. This includes the parameter designed to capture the exercise of market power. In the context of the standard specifications of models used to detect market power, this leads to a tendency to fail to reject the hypothesis of no market power. *Even when testing data generated such that market power is present, the exercise of market power is often not revealed in the highly aggregated data.*

In general, it appears that the researcher must be very careful when using econometric techniques to empirically test for market power. The models must be specified carefully, and a functional form must be chosen that is flexible enough to capture the unknown underlying technology. This is an aspect of this overall technique that has been largely ignored in previous research. In addition, if individual firm, or even plant, level data with observations consistent with the decision making time frame in the industry being studied are not available for the analysis, there is a high risk of obtaining a biased result regarding inferences an the exercise of market power.

Specific Conclusions Regarding Data Aggregation

When developing econometric models to be used for forecasting or policy analysis, it is important to determine if the aggregation level of the available data is appropriate for the analysis being conducted. If the available data are not consistent with the assumptions underlying the modeling effort, biased results could be obtained. Within the context of the present study, the probability of accurately inferring the exercise of market power based on the results of econometric behavioral models clearly changes when the data are aggregated over firms (decision makers), and over time. The magnitude of this change depends on several factors, including the amount of market power actually being exercised in the industry, the underlying technology of the industry, and the exact specification of the model used to test for market power. Models that in general do the best job of capturing the true data generation process at the disaggregate level do not reveal the same probability of correctly identifying market power when applied to aggregate data.

If the true underlying technology of the U. S. beef packing industry is not homogeneous (does not exhibit constant returns to scale), then the restrictive assumptions required for consistent data aggregation across firms, and over time, do not hold in this industry. In order to aggregate the data, there must be constant and equal marginal costs across firms and over time, and the quantity weighted conjectures or expectations regarding rival reactions must be equal. It is widely accepted that these restrictions do not completely hold for this industry, or any other industry subject to investigation. In spite of this observation, researchers have continued to use data aggregated over various dimensions to test for market power. What has not been previously determined is the magnitude of the information loss that can occur through aggregation when the underlying assumptions are not entirely valid. *This simulation has provided evidence to suggest that the information loss due to aggregation when the underlying technology is not homogeneous is sufficient to significantly change the results of market power tests as the aggregation level of the data is changed.*

Conclusions Regarding Functional Form

Perhaps even more dramatic than the differences across data aggregation levels were the differences in results between the three specifications of the market power testing model. The specifications differed in the functional form chosen to represent the cost function, which captures the underlying technology of the industry. When both the generalized Leontief and the quadratic functional forms were assumed to represent the cost function, the results were erratic and were not consistent with prior expectations. At all levels of data aggregation, these models tended to either reject the null hypothesis of no market power nearly all of the time, or none of the time, as underlying technologies varied when testing randomly generated data sets with no market power imposed. In addition, the results between aggregation levels were very erratic when testing the same underlying technologies and imposed behavior. On the other hand, the translog model performed largely as expected across the range of technologies tested. Though this model did tend to falsely reject the null more that the expected 5 percent of the time when testing disaggregate data generated to contain no market power, it did on average reveal the true underlying behavior much more consistently across the technology spectrum than the other two models. Also, when changing aggregation levels, the translog model tended to perform as expected depending on the returns to scale exhibited by the underlying technology. This is in contrast to both the generalized Leontief and the quadratic models, neither of which performed as expected.

This result is undoubtedly due to the fact that the translog is the most flexible of the three specifications investigated in this study. It clearly did a better job of capturing the true underlying structure of the data being tested, at all levels of aggregation. *The results of this study also indicate that the most commonly used functional form in previous NEIO econometric studies of behavior, the generalized Leontief, may be a poor choice for studies of market power. The evidence from this simulation suggests that the generalized Leontief specification is not flexible enough to adequately capture the underlying technology. Errors associated with improper choice of functional form appear likely to be allocated to the market power term when testing for non-competitive behavior in an econometric system.*

Policy Implications

Industrial organization researchers are interested in the measurement and empirical verification of non-competitive behavior in order to investigate public policy questions proposed by antitrust laws and regulations. In the past, the government regarded an industry with high values of concentration as a prime candidate for intervention. Under the present policy, high levels of concentration appear to more nearly target an industry for further investigation to determine if intervention is warranted. When an industry is selected for antitrust investigation, industry behavior plays an important role in the investigation. For example, sustained output pricing above the competitive level (referring to oligopoly behavior) is clearly spelled out as part of the criterion for allowance or disallowance of mergers in the new (1992) merger guidelines (Ordover and Willig). In addition, both section 2 of the Sherman antitrust act, and section 7 of the Clayton act, require proof of the exercise of market power before enforcement actions can be taken (Landis and Posner). During the course of an actual investigation, opposing sides must provide evidence regarding whether the feared anti-competitive behavior has or has not occurred, or will or will not occur.

In order to be consistent with these policies, investigations into market power issues will likely rely increasingly on empirical studies of individual industry behavior. Any real value of these studies for the purpose of

policy enforcement is clearly dependent on the accuracy and stability of the results. *The implication of this study is that researchers, and in turn policy makers, must be careful when relying on results of NEIO empirical econometric studies for policy enforcement.* The models upon which the respective studies are based must be carefully specified to assure that the true technology and underlying structure of the industry being analyzed are captured. In addition, the study must be conducted using disaggregate firm-level data with observations consistent with the time dimension in which input usage and output production decisions are made. Access to such hard to obtain, confidential data must accompany any request by policy enforcement agencies for an investigation into potential market power issues in any particular industry. There may need to be the potential for significant costs to society in terms of exercise of market power in a particular industry before the benefits of regulatory enforcement would outweigh the costs of obtaining the required data and performing the careful analysis needed to accurately identify non-competitive behavior.

Analysts and policy makers also need to keep in mind the following implication of this study. *Even when using essentially ideal disaggregate data and carefully specified models, there is a significant danger that the exercise of market power will be revealed by the analysis, when in fact no market power is being exercised.* In other words, to use a widely familiar analogy, there is a very real danger of essentially convicting an innocent industry when using econometric models of firm behavior to test for market power.

Future Research

This research was confined to a fairly narrow set of assumptions regarding industry structure, behavior, and technology. Before the results and implications garnered from this study can be broadly interpreted, similar studies should be conducted based on differing assumptions. For example, this study focused on market power in the primary input procurement market (oligopsony power). Though it is likely that the overall conclusions would be similar if data were simulated and tested for oligopoly power, this cannot be known for certain until the issues addressed here with regard to measuring oligopsony power are investigated with regard to oligopoly power, market power in the output market.

Simulating and testing data generated to represent other industries with a broad range of underlying structural characteristics, and a broader range of potential underlying technologies, would be useful. An additional interesting extension would be to simulate data such that some decision makers in the industry are exercising market power, and others are not, to determine how well models designed to test for the exercise of market power perform under these circumstances.

Another important dimension of data aggregation that was discussed briefly in earlier sections but not empirically investigated in this experiment, is the issue of aggregating specific inputs into groups. Fairly restrictive separability assumptions must hold in order to consistently combine specific inputs into broadly defined groups for econometric analysis. The degree to which these assumptions hold in the beef packing industry, or any other industry, is not completely known. More importantly, the consequences of violating these assumptions to various degrees in terms of parameter estimation bias in empirical studies, and in particular behavioral studies of market power, are not known. This would be an interesting, and important, direction for future research.

Finally, it is clear from the results presented in this study that model specification, and in particular functional form, is an important determinant of the success of efforts to econometrically test for market power. Even the most flexible of the three functional form specifications compared in this study (the translog) did not perform exceptionally well. Future research should be devoted to investigation of other alternative model specifications, and perhaps development of functions that are even more flexible than the translog, for incorporation into models of firm behavior. Obviously, it is very important that the true underlying technology of the industry being studied be adequately captured in studies of firm behavior. Efforts to improve the analysts ability to do so empirically would be a significant contribution.

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