Integrating the Structural Auction Approach and Traditional Measures of Market Power

Emílio Tostão
Department of Agricultural Economics
Oklahoma State University
535 Ag. Hall, Stillwater, OK 74078-6026
Email: emilio.tostao@okstate.edu

Chanjin Chung
Department of Agricultural Economics
Oklahoma State University
322 Ag. Hall, Stillwater, OK 74078-6026
Email: chanjin.chung@okstate.edu

B. Wade Brorsen
Department of Agricultural Economics
Oklahoma State University
414 Ag. Hall, Stillwater, OK 74078-6026
Email: wade.brorsen@okstate.edu

Selected Paper prepared for presentation at the American Agricultural Economics Association Annual Meeting, Long Beach, California, July 23-26, 2006.

Integrating the Structural Auction Approach and
Traditional Measures of Market Power

Abstract

This study asks the question, what is the relationship between traditional models of market power and structural auction models? An encompassing model is derived that considers both price markdowns due to bid shading during an auction and price markdowns at the industry-level due to imperfect competition. Data from a cattle procurement experimental market is used to compare the appropriateness of the two alternative theories. Regression results show that while the number of firms is more important than the number of bidders on lot of cattle in explaining pricing behavior in the game, the number of bidders does contain some unique information and should be included in the model. Both the traditional NEIO and structural auction approaches overestimated the true markdowns possibly due to failure to account for the winners curse.

Keywords

Bid shading, experimental cattle market, imperfect competition, price markdowns

Integrating the Structural Auction Approach and Traditional Measures of Market Power

Potential anti-competitive behavior of beef packers in cattle procurement markets has been well documented in recent years (Ward, 2002). Cattle producers contend that they receive lower prices for their cattle because packers act strategically to depress prices below price levels in competitive markets. For past decades, the national four firm concentration ratio has increased significantly from 25% in 1976 to about 80% in 1998 (Ward, 2002), which increases concern about possible packer market power in cattle procurement markets.

Most recent empirical studies of competition in cattle markets have used the new empirical industrial organization (NEIO) model (Schroeter, 1988; Azzam, 1997; Koontz and Garcia, 1997; Sexton, 2000; Paul, 2001; Lopez et al., 2002). The NEIO model seeks to explain market power originating from industry-level imperfect competition. A few empirical studies have looked at disaggregate measures of concentration such as the number of bidders at an auction (Meyer, 1988; Bailey, Ward, 1992; Brorsen, and Fawson, 1993; Bourgeon and Le Roux, 1996, 2001). These latter studies of market power use concepts from auction theory (Milgrom and Weber, 1982; Laffont and Vuong, 1996, Klemperer, 1999). The auction models seek to explain market power due to bid shading at local markets, such as cattle auctions (Bailey, Brorsen, and Fawson, 1993), rice auctions (Meyer, 1988), or grain auctions (Bourgeon and Le Roux, 1996; Banerji and Meenakshi, 2004). Auction models are agent-based models that enable estimation of market power considering the number of buyers, and sellers, and the bidding process at individual auctions.

Although the empirical literature has mostly used the NEIO model, the auction model seems more closely tied to the way cattle markets work since cattle buyers make a large number of individual purchase decisions rather than setting an equilibrium price. While NEIO models depend on the number of sellers and buyers in the industry, and use equilibrium prices determined by industry level demand and supply, auction models involve buyers and sellers arriving at a transaction price for a given quantity and quality of cattle at a given place and time. Thus, auction theory is associated with price discovery (i.e. focusing on microstructure), and the NEIO model is associated with price determination (i.e. focusing on macrostructure). These concepts are interrelated, but are not the same (Ward and Schroeder, 2001). Yet, previous studies seek to consider one market power effect or the other, not both. Which of these two models estimate market power more accurately? Should market power effects be added or do they measure the same thing? Answers to these questions require a model considering both auction theory's bid shading and industry-level imperfect competition. To our best knowledge, such a model has not been developed in the literature.

Therefore, this paper proposes an encompassing model that nests within it both auction theory's bid shading and NEIO's market-level imperfect competition. We derive an encompassing model by extending the traditional NEIO to formally include markdowns from both bid shading and market-level imperfect competition. The encompassing model derived in this paper is tested indirectly using data from an experimental cattle market. Results show that even though the number of firms in the experimental game is more important than the number of bidders on a lot of cattle, an encompassing model is preferred to either NEIO or auction model. Both NEIO overestimated the true price markdown possibly due to failure to account for the winners curse.

Market Power in Cattle Procurement Markets

The NEIO model and the auction model represent two major theories of possible market power in cattle procurement markets The NEIO theory, pioneered by Appelbaum (1982), posits that market power effects can be measured via "conduct parameters" estimated from a set of behavioral equations describing firm's production and pricing decisions (Bresnahan, 1989). The intuition behind the NEIO theory is that oligopsony power is inversely related to the number of firms in the (aggregate) industry, and depends on the conjectures adopted by the firms in the industry. Moreover, the theory posits that at any point in time firms make decisions using "equilibrium prices" determined by aggregate demand and supply.

Recent studies using the NEIO model to study competition in the U.S. cattle markets include Schroeter (1988), Azzam and Schroeter (1995), Koontz and Garcia (1997), Paul (2001), and Lopez, Azzam and Espana (2002). Most of these studies find little market power in cattle markets (Sexton, 2000; Ward, 2002). However, since the NEIO model seeks to measure market power due to industry-level imperfect competition, price markups due to bid shading are not explicitly considered.

The auction theory offers an alternative model about possible oligopsony power due to bid shading in auctions. Auctions are market institutions with an explicit set of rules that are used to elicit information, in the form of bids, from potential buyer regarding their willingness to pay for the good being auctioned (Krishna, 2002). Bidder's willingness to pay is a function of all available information to the bidder and the type of auction.

Auctions are widely used to sell agricultural commodities in local markets, and as such, they are important for the micro-level price discovery in agricultural markets. Prominent examples of agricultural commodities sold trough auctions in the U.S. are cattle (Crespi and Sexton, 2004), timber (Baldwin, Marshall, and Richard, 1997), and rice (Meyer, 1988). Moreover, auctions have also been used to allocate contracts for school milk in the U.S. (Porter and Zona, 1999), to sell flowers in the Netherlands (Klemperer, 1999), and to allocate wheat export contracts in Europe (Bourgeon and Le Roux, 1996, 2001). But, while a huge array of data are generated through auctions, few studies in the agricultural economics literature have used auction theory when examining competition in the U.S. food agricultural sector.

Bidders acting strategically may exert oligopsony power by shading their bids below their valuation, thereby depressing prices below price levels in competitive markets. However, there are several reasons why packers may bid less than their valuation other than active or passive collusion (Crespi and Sexton, 2004). Bidders may shade their bids to earn a positive margin, especially in procuring intermediate agricultural inputs or commodities for resale. Bidders may also shade their bids to avoid the winner's curse in auctions with common valuations. Conventions such as whole dollar bidding, reported in some cattle markets (Crespi and Sexton, 2004) and the NASDAQ (Christie and Schultz, 1994) may also lead to bid shading.

Bailey, Brorsen, and Fawson (1993) were among the first to use auction data to estimate market power in cattle markets. They used a single-equation (hedonic) regression of bids on lot characteristics and measures of concentration at local cattle auctions. Bailey, Brorsen, and Fawson (1993) found an increase in concentration at local auctions depressed cattle prices, but the effect was small. Crespi and Sexton (2004) also estimated a price-dependent hedonic regression to compare the buying pattern in the data with that predicted by their model. Using simulations, they found that the estimated model predicted a different buying and selling pattern from original the data.

This paper contributes to the literature in two areas. First, we consider an encompassing model that considers price markdowns due to auction's bid shading, and price distortions due to firm-level imperfect competition. Second, we provide fresh empirical results to the literature about market power estimation.

Structural Auction Model

This section outlines the structural auction model that has been used to estimate possible market power in cattle markets. Auction concepts were first proposed for empirical studies of price determination by Paarsch (1992), and extended by Guerre et al. (2000). Guerre et al. developed an equilibrium bidding model assuming first-price sealed-bid auctions with independent private values. We make a similar set of assumptions and justify them in the context of our experimental auction market.

The assumption of first-price sealed-bid auction implies that each bidder submits bids independently, and the bidder with the highest bid wins the auction and pays the amount of his bid. The first-price aspect emerges because the winner of good for sale is the packer with the highest bid. Our experimental cattle market is not a sealed-bid experiment but resembles it since bidders approach feedlots individually without knowing opponents' bid. Obviously, there are few instances where bidders can learn about rival's bids. Crespi and Sexton (2004) also assumed first-price sealed-bid auction assumption when studying packers' bidding behavior in the Texas Panhandle.

Our model also assumes that packers have independent private values (IPV). The IPV assumption implies that (a) bidder's valuation is unique and privately known to the bidder, and (b) the valuations are drawn independently from a common distribution known to all packers. While the more general case of affiliated or correlated values (i.e. bidder's valuation has both private and common values) would be more adequate for our experimental cattle market, the IPV assumption is not inconsistent with the factors influencing bidders valuations in cattle markets, including our experimental cattle market. To see why, define each packer's valuation for a lot of cattle as the difference between the price beef and the price of cattle. Then, to the extent processing costs are unique to each packer and known only to the packer, there is an IPV component to the valuation (Banerji and Meenakshi, 2004). Furthermore, as long as bidders have the same information about the common aspects and place similar weight on it, then the IPV assumption is not very restrictive (McAfee and McMillan, 1992). A further reason to assume IPV is the simplicity it lends to our model.

We also assume repeated auctions rater than simultaneous auctions. This assumption fits well our experimental cattle market and helps simplify the model. This is because some real world cattle markets are characterized by repeated interaction of buyers. The cattle market in the Texas Panhandle is an example of a local market where few buyers (three packers) interact repeatedly in procuring cattle via first price sealed-bid auctions (Crespi and Sexton, 2004).

To illustrate the auction model considered in this study, consider a cattle market with few packers purchasing cattle through a sequence of first-price sealed-bid auctions in the context of IPV. Packers' valuation (R_{ij}) is defined as the price of processed beef (p_j^r) minus the marginal cost (c_{ij}) of processing cattle into beef. That is $R_{ij} = p_j^r - c_{ij}$. Although competing packers do not know opponents' valuation, they know that all valuations R, including their own, come from a common distribution $G(\bullet)$ which is continuous with density $g(\bullet)$.

As discussed previously, packer's valuation depends on the processing technology employed. Following Sexton (2000), we assume that beef packers use cattle and non-farm processing inputs to produce beef, y^r, using a quasi-fixed proportion processing technology. Such technology allows no substitution between cattle, y^f, and a vector of non-farm inputs, **v**, but may allow substitution between non-farm inputs. Processors' technology is represented as:

$$y^r = \min\{y^f/\gamma, g(\mathbf{v})\}, \tag{2.1}$$

where $\gamma \le y^f/y^r$ is the conversion factor between cattle and processed product. Packer's profit maximization requires that $y^r = y^f/\gamma = g(\mathbf{v})$.

In maximizing expected profits, π_i, the ith risk-neutral packer faces the following maximization problem (Bajari and Hortaçsu, 2005):

$$\max_{p_{ij}^f} \ \pi_{ij} = y_{ij}^r (R_{ij} - p_{ij}^f) G(\varphi(p_{ij}^f))^{N_j - 1}, \tag{2.2}$$

where i ($i = 1,\ldots, I$) is a subscript for packer, and j ($j = 1,\ldots, T$) is a subscript representing the jth cattle lot, $R_{ij} = p_j^r - c_{ij}$ is packer i's per-unit valuation of processed product y_{ij}, produced at processing cost c_{ij}, and sold at price p_j^r; p_i^f is packer i's dollar bid for cattle,

$\varphi(p_{ij}^f)$ is the inverse of the equilibrium bid function, $G(\varphi(p_{ij}^f))^{N_j-1}$ is the probability that packer *i* wins the auction of the *j*th lot of cattle, and N_j is the number of packers bidding for the *j*th lot of cattle.

The first-order condition for maximizing packer's profits is:

$$\frac{\partial \pi_{ij}}{\partial p_{ij}^f} = 0 = -y_{ij}^r G(\varphi(p_{ij}^f))^{N_j-1} + y_{ij}^r (N_j - 1)(R_{ij} - p_{ij}^f) G(\varphi(p_{ij}^f))^{N_j-2} \frac{\partial G(\varphi(p_{ij}^f))}{\partial p_{ij}^f} \tag{2.3}$$

$$= y_{ij}^r G(\varphi(p_{ij}^f))^{N_j-1} + y_{ij}^r (N_j - 1)(R_{ij} - p_{ij}^f) G(\varphi(p_{ij}^f))^{N_j-2} g(\varphi(p_{ij}^f)) \frac{\partial \varphi(p_{ij}^f)}{\partial p_{ij}^f} = 0,$$

which can be re-arranged and rewritten as:

$$p_{ij}^f = R_{ij} - \frac{F(p_{ij}^f)}{f(p_{ij}^f)(N_j - 1)}, \tag{2.4}$$

where $f(p_{ij}^f) = g(\varphi(p_{ij}^f))\partial\varphi(p_{ij}^f)/\partial p_{ij}^f$ and $F(p_{ij}^f) = G(\varphi(p_{ij}^f))$ are bid density and distribution functions evaluated at p_{ij}^f.

Equation (2.4) shows that packer's strategic behavior could yield bids below packer's valuation R_{ij}. The markdown or bid-shading factor is represented by the second member of the right hand side of equation (2.4) (Hortaçsu, 2002). Notice that the bid-shading factor is inversely related to the number of bidders N_j bidding for the *j*th lot of cattle rather than the number of firms in the industry. The bid-shading factor approaches zero as the number of bidders for lot *j* approaches infinity.

The NEIO Model

This section outlines the NEIO model about possible market power in cattle procurement markets. This theory was proposed by Appelbaum (1982) and Bresnahan (1989). Unlike the auction model, NEIO measure of market power depends on the number of firms in the industry rather than the number of bidders for a particular lot of cattle. In addition, packers are assumed to make their decision based on "equilibrium" cattle prices determined by aggregate demand and supply (i.e. there are no losers and winners as was the case for the auction model).

Characterization of packer's strategic behavior within the NEIO model is achieved via "conjectural variations" representing firm's best guess about competitors' response to a change in purchases of cattle. These conjectural variations are derived from the first-order condition of packer's profit maximization. Subsequent aggregation of firm behavior yields an industry supply equation incorporating industry-level conjectural variations.

To illustrate the concepts of the NEIO model, consider the same beef processing industry described previously, and assume that farm input producers compete perfectly and supply farm inputs to packers via an inverse supply function represented as:

(2.5) $$p^f = \sum_{j=1}^{J} p_{ij}^{wf} / J = S(Y^f \mid \zeta),$$

where p^f is the average price of cattle in the industry, J is the number lots sold, p_{ij}^{wf} is the winning bid for the jth lot of cattle, Y^f is the total supply of cattle, and $\boldsymbol{\zeta}$ is a vector of supply shifters.[1] Notice that $Y^f = \sum_i^n y_i^f$ $Y^f = \Sigma y^f$, where y_i^f is the quantity of cattle purchased by packer i.

[1] Notice that market level (equilibrium) price of cattle p^f in (2.5) is not equal to the transaction-level price of cattle p_{ij}^f in (2.4). The former is the average of winning bids in J cattle auctions (transactions), while the latter includes losing bids. Thus $p^f = \sum_{j=1}^{J} p_{ij}^{wf} / J$, where p_{ij}^{wf} is the winning bid.

As was with the auction model, packers' processing technology is assumed to be of Generalized Leontief form. For simplification, the conversion factor to convert cattle into boxed beef is assumed to be one. Thus, $y^f = y^r = y$.

The profit maximization problem for packer *i* is represented as:

$$\max_{y_i^r} \quad \pi_i = [p^r - p^f(Y^f)]y_i^r - C(y_i^r, \mathbf{v}). \tag{2.6}$$

where π_i is packer *i's* profit, p^r is the retail price of beef, and $C(y_i^r)$ is the processing cost function for a representative packer. The first order condition for maximizing equation (2.6) is:

$$\frac{\partial \pi_i}{\partial y_i^r} = p^r - \frac{dp^f(Y^f)}{dY^f}\frac{\partial Y^f}{\partial y_i^r} y_i^r - p^f - \frac{\partial C(y_i^r, \mathbf{v})}{\partial y_i^r} = 0.$$

Rearranging and re-writing the first order condition yields:

$$p^r = p^f[1 + \frac{(1+\theta_i)s_i}{\varepsilon_s^f}] + c(y_i^r), \tag{2.7}$$

where $c(y_i^r) = dC(y_i^r, \mathbf{v}) / dy_i^r$ is packer *i*'s marginal cost of processing beef, $\varepsilon_s^f = (dY^f / dp^f)(p^f / Y^f)$ is elasticity of cattle supply, $s_i = y_i^r \big/ Y^r$ processor *i*'s market share, and $\theta_i = d\sum_{i \neq j}^n y_j^f / dy_i^r$ is packer *i*'s conjecture about rivals' responses to its change in purchases of cattle.

Customary with the NEIO model, an industry pricing equation is obtained from equation (2.7) after multiplying every term of (2.7) by each firm's market share s_i, and summing across all processors in the industry as:

$$\sum_i^n s_i p^r = \sum_i^n s_i p^f + \sum_i^n \left(\frac{(1+\theta_i)s_i s_i}{\varepsilon_s^f} p^f \right) + c(y_i^r). \tag{2.8}$$

Re-arranging (2.8) equation yields the industry pricing equation:

(2.9) $$p^r = p^f[1 + \frac{(1+\Theta)HHI}{\varepsilon_s^f}] + c(Y^r),$$

where $\Theta = \sum_i (y_i^r)^2 \theta_i / \sum_i (y_i^r)^2$, is the industry weighted conjectural variation in the farm-input market, $c(Y^r)$ is industry level processing cost, and $HHI = \sum_i s_i^2$ is the Herfindahl index in the processing sector.

Equation (2.9) shows the NEIO measure of industry oligopsony power is directly related to both industry concentration (*HHI*), and weighted firm-conjectures about how competitors respond to a change in purchases of cattle (Θ). The industry conjectural variation Θ is equal to zero under the Cournot-type competition, minus one under perfect competition, and one under perfect collusion.

The difference between oligopsony power from the NEIO model and oligopsony power from the structural auction model can be emphasized by separating the price markdown in equilibrium equations (2.4) and (2.9) respectively, as:

(2.4a) $$R_{ij} - p_{ij}^f = p_j^r - c_{ij} - p_{ij}^f = \frac{F(p_{ij}^f)}{f(p_{ij}^f)(N_j - 1)},$$

and,

(2.9a) $$p^r - c(y_i^r) - p^f = [p^f \frac{(1+\Theta)HHI}{\varepsilon_s^f}].$$

As shown in equations (2.4a) and (2.9a), while the markdown derived with the auction theory, $F(p_{ij}^f) f(p_{ij}^f)(N_j - 1)$, depend on the number of bidders on a particular lot of cattle (N_j), the markdown derived with the NEIO theory depends on the number of packers in the industry (n), since $HHI = \sum_i s_i^2 = (y_i^r / Y_i^r)^2 = (1/n)^2$, and the type of packer's conjectures about rivals response to change in purchases of cattle

$\theta_i = d\sum_{i \neq j}^{n} y_j^f / dy_i^r$. Clearly, these two models seek to measure different market power effects.

Encompassing Model of Bid Shading and Industry Level Imperfect Competition

The previous two sections outlined the structural auction and the NEIO models regarding potential oligopsony power in cattle procurement markets. The auction theory estimates transaction level oligopsony markdowns, and the NEIO approach estimates market level oligopsony markdowns.

This section proposes an encompassing model that incorporates markdowns from both bid shading and industry-level imperfect competition. As mentioned previously, bid shading in auctions and market-level imperfect competition are different concepts, but could be nested within the same model.

The encompassing model proposed here is an extension of the NEIO model to incorporate both market powers from bid shading and from industry level imperfect competition. To illustrate the intuition behind our model, consider a cattle market where packers procure cattle through first-price sealed-bid auctions. As noted previously, the number of bidders for a particular lot of cattle does not necessarily equal the number of firms in the industry. Furthermore, assume that packers bidding for the jth cattle lot may act strategically and bid below their valuation by the amount δ_{ij}, given by the right hand-side of equation (2.4a). Thus, the price p_{ij}^f paid by a winning bidder is equal to bidder's valuation V_{ij} minus the shading factor δ_{ij}. Recall that the valuation V_{ij} is defined as the difference between wholesale price of beef minus the processing cost ($V_{ij} = p_j^r - c_{ij}$).

If bid shading is zero (i.e. $\delta_{ij} = 0$), then price markdown from the NEIO model is the "true" markdown that the NEIO model seeks to explain. This markdown is represented by the right hand side of equation (2.9a). Denote this markdown by *M*. However, if bid shading is not zero, then the markdown estimated with the NEIO approach contains the "true" markdown (*M*) that the NEIO model seeks to explain plus some bid shading δ_j ($\delta_j = \Sigma\delta_{ij}/J$). Denote this markdown by $\widetilde{M}$. Mathematically, the relationship between $\widetilde{M}$ and *M* is:

(2.10)
$$\widetilde{M} = M + \delta_j,$$

where $\widetilde{M}$ is the "mixed" markdown containing the "true" markdown (*M*) that the NEIO seeks to explain plus the average bid shading on *J* total cattle lots δ_j ($\delta_j = \Sigma\delta_{ij}/J$).

Therefore, in the presence of bid shading, the industry-pricing rule represented by equation (2.4a) can be rewritten as:

(2.11)
$$p^r - c(Y^r) - p^f = \begin{cases} M, \text{ if } \delta_\mathrm{j} = 0 \\ \widetilde{M}, \text{ if } \delta_\mathrm{j} \neq 0. \end{cases}$$

where $\widetilde{M} = p^f(1+\widetilde{\Theta})HHI/\varepsilon_s^f$, $\widetilde{\Theta}$ is a "mixed" conjectural variation when bidders bid shading is not zero, $\delta_j = \sum_{j=1}^{J}[F(p_{ij}^f)/f(p_{ij}^f)(N_j - 1)]/J$, and $M = \widetilde{M} - \delta_j$. The relationship between the industry conjectural variation (Θ) in *M* (when there is no bid shading) and the "mixed" conjectural variation $(\widetilde{\Theta})$ in $\widetilde{M}$ (when there is bid shading) can be expressed as:

(2.12)
$$\underbrace{p^f \frac{(1+\widetilde{\Theta})HHI}{\varepsilon_s^f}}_{\widetilde{M}} = \underbrace{p^f \frac{(1+\Theta)HHI}{\varepsilon_s^f}}_{M} + \delta_j,$$

which can be re-arranged to yield:

(2.12a)
$$\widetilde{\Theta} = \Theta + \delta_j \frac{\varepsilon_s^f}{p^f\, HHI}.$$

Equation (2.12a) shows that when both bid shading and industry level imperfect competition are considered, the conjectural variation obtained with the NEIO model is a "mixed" conjectural variation $(\widetilde{\Theta})$ given by the sum of the "true" conjectural variation (Θ) and the average bid shading δ_j, weighted by the ratio of elasticity of cattle supply to the price of cattle times the Herfindahl index $(\varepsilon_s^f / (p^f HHI))$.

The encompassing model considering both bid shading and industry level imperfect competition is obtained by substituting equations (2.12a) and (2.12) back into the industry supply equation (2.9a) to yield:

$$p^r - p^f - c(Y) = [p^f \frac{(1+\Theta)HHI}{\varepsilon_s^f}] + \delta_j \frac{\varepsilon_s^f}{p^f HHI}, \tag{2.13}$$

The model represented by equation (2.13), is more general than the models represented by equations (2.4a) and (2.9a) since it nests both (2.4a) and (2.9a). Industry-level imperfect competition, which the NEIO model seeks to explain, is captured by Θ, the industry conjectural variation. The price markdown considered by the auction model is represented by the bid shading factor δ_j.

Notice that if $\delta_j = 0$, there is no bid shading, and all perceived price markdown is due to industry level imperfect competition. In this case, equation (2.13) becomes equation (2.9a). If $\Theta = 0$ and $\delta_j \neq 0$, equation (2.13) becomes equation (2.4a), and all perceived price markdown is due to bid shading. If $\Theta \neq 0$ and $\delta_j \neq 0$, then perceived price markdown are due to both bid shading and industry level imperfect competition.

Data and Empirical Application

This section uses data from a cattle procurement experiment to test the encompassing model proposed in the previous section. The cattle experiment is described first, followed by an empirical procedure to test the theory. The data only allow for an indirect test rather than a direct test using equation (2.13). We also estimate markups using the both traditional NEIO model and a structural auction model, and compare these markups with the markups estimated directly from the data.

Data

The data used in this study were generated from a five-hour evening workshop using the *Fed Cattle Market Simulator* (FCMS) (Hogan et al., 2003; Ward, 2005) in February, 2006. The FCMS simulates a market for fed cattle that mimics the real-world cattle procurement market. Some of the participants in the FCMS play the role of feedlot managers while others the role of meatpackers

The participants in our experiments were primarily undergraduate students majoring in agricultural economics. The students were organized in four packer teams (each with four members) and eight feedlot manager teams (each with 3 or 4 members). In addition, one "observer" was allocated to each feedlot with the exclusive task of recording all bids, both winning and losing bids, submitted by packers. The observers recorded bids on special paper cards, and did not participate in cattle trades. The data recorded at each feedlot consisted of price and quality of cattle sold, and identity of feedlots and buyers.

During the experimental game, packer and feedlot teams are instructed to maximize profits. Both packers and feedlot managers were instructed to buy and sell cattle for profit. Competition among teams was stimulated by paying a $40 participation fee per person with the opportunity to win more or lose part of the fee based on financial performance during the game.

Each member of a packer team was assigned to a feedlot and instructed to act as a regional buyer, just like in real cattle procurement markets. This was intended to allow enough time for packers to inspect and submit bids for cattle among spatially dispersed feedlots. Each trading period lasted about ten minutes and was called a "week." The winner of each auction was the packer who submitted the highest bid.

During the trading period, paper cards representing completed trades are returned to the instructors who scanned them into a computer. The information on each card from a completed trade includes the price and quality of cattle sold, and identity of the seller and the buyer. This information is summarized for market participants before the next trading period. Thus, feedlots and meatpacking managers are informed about the volume of cattle trade, cattle placed on feed, and the wholesale price of processed beef in the previous trading period.

A total of 1,788 transaction data were collected during fourteen trading weeks, after allowing for a training period of two weeks. After the first seven weeks of cattle trades, two mergers were simulated. Packer one merged with Packer two, and Packer three merged with Packer four. These mergers represented the smallest packers (1 and 2) and the largest packers (3 and 4). Overall, the structure of the game remained essentially the same after the mergers except that there were two bigger packers instead of four smaller ones. Descriptive statistics of the variables used in the analysis are reported in table 1.

As reported in table 1, the average cattle price after adjusting for dressing percentage (121$/cwt) is greater than the price of beef (119$/cwt). Further, the spread between boxed beef price and the dressed cattle price is negative in 536 out of 1066 transactions, suggesting that packers lost money in about half of the transactions. This suggests that market power, if any, is expected to be small.

An Indirect Test of the Encompassing Model

This section tests outlines the procedures to test our encompassing model. The test is based on a single-equation regression of price spread on number of bidders and market-level concentration. The test whether the hypothesis that an aggregate model (i.e. the NEIO model) is consistent with the data against the hypothesis that the disaggregate model (i.e. the structural auction model) is consistent with the data. This is a rather indirect test. A direct test of our theory using equation (2.13) would require estimating a bid-shading factor using the auction model, and use this estimate as an explanatory variable in our NEIO like regression in the second step. Notice that estimation of bid shading using equation (2.4a) requires data with at least two bidders in every transaction. However, our experimental data contained numerous transactions with only one bidder, precluding a meaningful estimation of markups using the structural auction model. This is limitation of the structural auction model.

The test of an aggregate model against a disaggregate model is nonnested because, in principle, neither of the two models can be obtained from the other by imposing restrictions on parameters of either model. The encompassing test considered here consists of artificially nesting the two candidate models within a single model, and then carry out hypotheses tests.

The candidate models are single-equation regressions of a packer margin (i.e. price spread between wholesale beef price and bid price) on a set of explanatory variables. The encompassing model ($M3$) nests models ($M1$) and model ($M2$). Model

$M1$ represents a disaggregate model such as an auction model, and model $M2$ represents an aggregate model such as the traditional NEIO model. To account for weekly changes in demand and supply of cattle that are observed imperfectly within the experimental cattle market, an additional error term is appended to the nested model ($M3$) to capture these time random effects, as:

$$\begin{aligned} M3: \quad p_{jt}^{r} - p_{jt}^{wf} = \omega_0 &+ \omega_1 shwlst_{jt} + \omega_2 todem_{jt} + \omega_3 fdlt1_{jt} + \omega_4 fdlt2_{jt} + \omega_5 fdlt3_{jt} \\ &+ \omega_6 fdlt4_{jt} + \omega_7 fdlt5_{jt} + \omega_8 fdlt6_{jt} + \omega_9 fdlt7_{jt} + \omega_{10} GenM_{jt} \\ &+ \omega_{11} GenH_{jt} + \omega_{12} wt1150_{jt} + \omega_{13} wt175_{jt} + \omega_{14} bid1_{jt} \\ &+ \omega_{15} bid2_{jt} + \omega_{16} bid3_{jt} + \omega_{17} HHI_{jt} + \eta_t + \varepsilon_{jt}. \end{aligned}$$

where subscript j represents a lot of cattle, subscript t indicates a week within which the jth lot is sold p_j^r is beef price, p_j^{wf} is winning bid, $todem_j$ is total demand for cattle, $fdlt1$, $fdlt2$, $fdlt3$, $fdlt4$, $fdlt5$, $fdlt6$, and $fdlt7$ are zero-one indicator variables that equal one if the cattle are bought from feedlots 1, …, 7, respectively; *shwlst* is the inventory of cattle available for sale in a given week, $wt150$, and $wt175$ are zero-one indicator variables that equal one if steer's weight is 1500, and 1175 lbs., respectively; *GenM*, and *GenH* are zero-one indicator variables that equal one if the generic type of carcass quality is medium, and high, respectively; $bid1$, $bid2$ and $bid3$ are zero one indicator variables that equal to one if there were one, two, or three bidders on the lot; *HHI* is industry concentration, the ω_{jt}'s are parameters to be estimated, $\eta_t \sim N(0, \sigma_\eta^2 I_n)$ is a week specific random error term to capture imperfectly measured changes in weekly demand and supply of cattle, $\varepsilon_{jt} \sim N(0, \sigma_{\varepsilon_{jt}}^2 I)$, is a observation- specific error term that accounts for possible heteroskedasticity inherent to time-series cross-sectional data, with $\sigma_{\varepsilon_{jt}}^2 = \exp(b_0 + b_1 shwlst_{jt} + b_2 todem_{jt})$ and $\mathrm{cov}(\varepsilon_{jt}, \eta_t) = 0$. Notice that models $M1$ and

*M*2 are similar to *M*3 except that *M*1 does not include HHI_{jt}, and *M*2 does not include *bid*1, *bid*2, and *bid*3. Variance components model (*M*3) was estimated via maximum likelihood (ML) using the NLMIXED Procedure in SAS 9.1 (SAS 2001-2003).

There are two null hypotheses of interest in model *M*3. The first null hypothesis is that the coefficients for *bid*1, *bid*2 and *bid*3 are jointly zero $(H_{01} : \omega_{14} = \omega_{15} = \omega_{16} = 0)$. The second null hypothesis is that the coefficient for *HHI* is zero $(H_{02} : \omega_{17} = 0)$. If both H_{01} and H_{02} are rejected, then number of bidders and the number of firms contain unique information, and suggest an encompassing model (*M*3) rather than either model *M*1 or *M*2. If both H_{01} and H_{02} are not rejected, then the number of bidders and the number of firms contain the same information and either aggregate or disaggregate model could be used. If only H_{01} is rejected then a disaggregate model is favored, while if only H_{02} is rejected an aggregate model is favored.

Estimation of a Structural Auction Model

This section reports the procedures used to estimate packer's bid shading using the structural auction model represented by equation (2.4a). The estimate of the auction model is compared with an estimate of price markdowns computed directly from the data. The estimation considers the number of potential bidders rather than the actual number of bidders. This was due to the presence of numerous transactions where only one bidder submitted a bid, which precluded estimation of bid shading using equation (2.4a).

The estimation of packer's bid shading in equation (2.4a) uses the nonparametric approach for estimating the structural auction model proposed by Guerre et al. (2000). As equation (2.4a) shows, packer's bid shading is the ratio of the bid probability distribution $F(p_{ij}^{f})$ to the product between bidders' density function $f(p_{ij}^{f})$ and the number of bidders on a given lot of cattle (N_j). Following Guerre et al. (2000), the estimates of bid cumulative distribution and density functions are obtained via the empirical distribution $\hat{F}(p_{ij}^f)$ and kernel density estimator $\hat{f}(p_{ij}^f)$, respectively as:

(2.14) $$\hat{F}(p_{ij}^f) = \frac{1}{MJ}\sum_{i=1}^{M}\sum_{j=1}^{J} I(p_{ij}^f \le p^f),$$

(2.15) $$\hat{f}(p_{ij}^f) = \frac{1}{MJh}\sum_{i=1}^{M}\sum_{j=1}^{J} K\left(\frac{p^f - p_{ij}^f}{h}\right),$$

where h is a *bandwidth* defining the size of the "neighborhood" around and arbitrary bid p^f, p_{ij}^f is the jth bid in the interval (p^f - h, p^f + h), J is the total number of cattle lots, and $K(\bullet)$ is the kernel density function, which assigns weights to every bid in the neighborhood of p^f.

The kernel density function defined by equation (2.15), is estimated assuming a Gaussian kernel function as:

(2.16) $$K(u) = \frac{1}{\sqrt{2\pi}}\exp(-\frac{1}{2}u^2), \text{ where } u = \left(\frac{p^f - p_{ij}^f}{h}\right).$$

Previous studies indicate that while the choice of the form of the kernel functional form does not affect results in practice, the choice of the bandwidth (h) may affect results (DiNardo and Tobias, 2001; Härdle et al., 2004). Sheather (2004, p.596) recommends the Sheather-Jones plug-in method (SJPI) due to good performance. The SJPI is defined as:

(2.17) $$h = \hat{\sigma}(4/3J)^{1/5},$$

where $\hat{\sigma}$ is sample standard deviation of the bids and J is the number of bids in the sample. The kernel density function is estimated using the KDE Procedure in SAS 9.1.

The option METHOD = SJPI in the KDE Procedure is used to request bandwidths computed using the SJPI.

Next, the estimates of bid shading for each successful transaction are computed using equation (2.4a), as:

$$\hat{p}_j^r - \hat{c}_{ij} - \hat{p}_{ij}^{wf} = \hat{\delta}_{ij} = \frac{\hat{F}(p_{ij}^{wf})}{\hat{f}(p_{ij}^{wf})(N-1)}. \tag{2.4b}$$

where p_{ij}^{wf} is a winning bid on the *j*th lot of cattle won by packer *i*.

Estimation of a Traditional NEIO Model

This section reports the procedures used to estimate markups using a traditional NEIO model represented by equation (2.9a). The estimate of the auction model is compared with an estimate of price markdowns computed directly from the data.

Before equation (2.9a) can be estimated, however, it is necessary to define packers' processing cost equation. Following Azzam (2001), packer's processing cost function $C(y_i^r)$ is represented by the Generalized Leontief, as:

$$C(y_i^r, \mathbf{v}) = y_i^r \sum_k \sum_m \alpha_{km} (v_k v_m)^{1/2} + y_i^r t \sum_k \lambda_k v_k + (y_i^r)^2 \sum_m \beta_k v_k, \tag{2.18}$$

where y_i^r is packer *i*'s output, $\mathbf{v}$ is a price vector of non-farm inputs such as labor and capital, *t* is a time trend, and α_{km}, λ_k, and β_k are parameters to be estimated. Notice that, with the exception of cattle, all non-farm inputs needed for beef processing remain constant in the experimental market. Therefore, packer's processing cost represented by

(2.16) reduces to $C(y_i^r) = \alpha_{km} y_i^r + \lambda_k y_i^r t + \beta_k (y_i^r)^2$, which is simply a quadratic cost function.

The industry marginal cost $c(Y^r)$, required to estimate industry-level markups represented by equation (2.13), is obtained in the following way. First, we differentiate packer's processing cost equation (2.16) with respect to output to get a firm-level marginal cost, as $c(y_i^r) = \partial C(y_i^r) / \partial y_i^r = \beta_0 + 2\beta_{1k} y_i^r$. For convenience, industry marginal cost can simply be represented as:

(2.19) $$c(y_i^r) = 2y_i^r.$$

Next, we obtain the industry marginal cost equation by multiplying every term of (2.19) by each firm's market share s_i, and summing across all processors in the industry, as:

$$\sum_i^n s_i c(y_i^r) = 2\sum_i^n s_i y_i^r,$$

which can be re-arranged to yield the industry marginal cost function, $c(Y^r)$, as:

(2.20) $$c(Y^r) = 2Y^r HHI.$$

Lastly, the industry pricing equation used to estimate oligopsony power is obtained by re-arranging equation (2.9a), after replacing $c(Y^r)$ with equation (2.20), as:

(2.9b) $$p^r = p^f [1 + \frac{(1+\Theta)HHI}{\varepsilon_s^f}] + 2Y^f HHI,$$

where $\hat{\delta}$ is a transaction level average bid shading estimated with the structural auction approach described previously.

Empirical estimation of equation (2.9b) also requires knowing the elasticity of cattle supply. The elasticity of cattle supply could be obtained from a cattle supply equation, which is estimated jointly with equation (2.9b). However, a system of equations containing equation (2.9b) and a supply equation was not well identified since there was no variable in the demand equation that was not in the supply equation. Following Paul's (2001) suggestion, equation (2.9b) was estimated alone assuming several values for cattle supply elasticity (0.2, 0.4, 0.8 and 1). Specifically the following equation was estimated:

$$p_t^r = a_0 + p_t^f[1 - \frac{(1+\Theta)HHI_t}{\varepsilon_s^f}] + a_1 HHI_t(Y_t^f / SHOW_t) + v_t \qquad (2.21)$$

where p_t^r is the average price of boxed beef in week t, p_t^f is the average cattle dressed price, $SHOW_t$ is the total inventory of cattle in the show list a_0, a_1, a_2 and Θ are parameter to be estimated, and v_t, is a error term.

To account for possible measurement error and endogeneity that leads to inconsistent OLS because $E[u_t x_t] \neq 0$, e quation (2.21) is estimated by nonlinear two-stage least squares (N2SLS) using the MODEL Procedure, SAS 9.1 (SAS Institute, 2002-03). The N2SLS estimator is consistent and asymptotically efficient when endogenous variables are correlated with error terms (Zellner and Theil, 1962).

Results

Maximum likelihood estimates of the encompassing model represented by equation (2.13) are shown in table 2. The estimates of interest are the coefficients of the Herfindahl index $(\hat{\omega}_{17} = 11.95)$, and the coefficient for indicator variables for one bidder $(\hat{\omega}_{14} = 0.47)$, two bidders $(\hat{\omega}_{15} = 0.38)$, and three bidders $(\hat{\omega}_{16} = 0.38)$. These coefficients are significant at the 10% level, except the coefficient for the indicator variable when for one bidder. Theory predicts that the price spread between beef price and cattle price should decrease as the number of firms or/and the number of bidders decreases. Therefore, the coefficient for *HHI* and the coefficients for number of bidders have the correct positive signs. The coefficient for number of bidders is correct because the reference is the indicator variable for four bidders. Thus, as expected, results show that the price spread between price of price of beef and cattle increases as the number of bidders decrease.

However, while the coefficient for *HHI* and the coefficients for number of bidders have the correct sign, the coefficient for *HHI* is least twenty times bigger than the coefficients of indicator variables for number of bidders. This suggests that the number of firms is more important in explaining price markups than the number of bidders for a particular lot of cattle. Thus, an aggregate model (such as NEIO) seem relatively more consistent with the experimental data than a disaggregate model (such as structural auction model).

The null hypothesis that an aggregate model (*M*2) is the correct model (H_{01}: *bid*1 = *bid*1 = *bid*1 = 0) is rejected at the 5 % level based on a likelihood ratio (LR) test, since LR = -2[log-likelihood *M*1- log-likelihood *M*3] = 10.2 $> \chi^2_{3,0.05}$=5.99. The null hypothesis that a disaggregate model (*M*1) is the correct model $(H_{02} : HHI \leq 0)$ is also rejected at the at the 5% level based on a one tailed *t*-test ($t = 1.98 > 1.75 = t_{16,\ 0.05}$). Thus, although size of the coefficients showed that the number of firms in the experimental game is more important than the number of bidders for a particular lot of cattle, the number of bidders does contain some (unique) information about pricing behavior in the game. Results suggest that both the number of firms and bidders should be considered in the estimation. Thus, there is some gain from considering both traditional NEIO and auction measures of market power within the same model.

Estimates of price markdown estimated with the structural auction model and traditional NEIO model are shown in tables 3 and 4 respectively. The structural auction's average markdown for all bidders shown in table 3 is \$3.36 per cwt, and the average markdown obtained with the traditional NEIO approach is \$2.7 per cwt. Both the NEIO and the structural auction approach seem to overestimate the true markdown because the average markdown estimated directly from data is nearly zero. Packers profit, given by the difference between average price spread (\$1.22 cwt) minus the average marginal cost (roughly estimated at \$5 cwt), is negative (-\$4.78 cwt). Thus, it is unlikely that packers in the game could have positive markdowns as suggested by the traditional NEIO and the structural auction approach.

Estimates of price markdowns using the NEIO and structural auction approach are not consistent regression results from the encompassing equation (2.13). The regression results suggest much more difference between price markdowns the estimated with NEIO and structural auction approach that it is actually found. One possible explanation for this discrepancy in results is failure of the two approaches to account for the winner's curse. The price spreads estimated directly from data reveal that packers lost money in about half of the transactions. Other possible source of bias for the structural auction approach is use on potential number of dibbers than the actual number of bidders, and failure to account for refusal to sale.

Conclusion

Recently, there have been many studies evaluating potential market power in the U.S. cattle procurement markets. These studies used either the NEIO model or the auction model. However, price markdown measures from these two approaches are not the same.

While the NEIO model seeks to measure price distortions due to industry-level imperfect competition, the auction models consider price distortion from bid shading at local auctions. A formal model considering both types of price markdowns has not been developed.

The encompassing model proposed in this study that considers both price markdowns from bid shading and price markdowns due to industry-level imperfect competition. An indirect test of our model showed that the number of firms in the experimental game is more important than the number of bidders on a lot of cattle in explaining price markdowns in the experimental game. However, results also show that the number of bidders on a particular lot of cattle contains some unique information and should not be neglected. Thus, while an aggregate model seems more appropriate than a disaggregate model, an encompassing model similar to the one proposed in this study, seems even better. Both the NEIO and structural auction failed to account for the winners curse, and overestimated the "true" markups considerably.

References

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

Azzam, A.M. 1997. "Measuring Market Power and Cost-Efficiency Effects of Industrial Concentration." *The Journal of Industrial Economics* 45: 377-386.

Azzam, A.M., and J.R. Schroeter. 1995. "The Tradeoff between Oligopsony Power and Cost Efficiency in Horizontal Consolidation: An Example from Beef Packing." *American Journal Agricultural Economics* 77: 825-836.

Bailey, D.V., B.W. Brorsen, and C. Fawson. 1993. "Buyer Concentration at Feeder Cattle Auctions." *Review of Agricultural Economics* 15: 103: 119.

Bajari, P., and L. Ye. 2003. "Deciding between Competition and Collusion." *The Review of Economics and Statistics* 85: 971-989.

Bajari, P., and A. Hortaçsu. 2005. "Are Structural Estimates of Auction Models Reasonable? Evidence from Experimental Data." *Journal of Political Economy* 113: 703-741.

Baldwin, L.H., R.C. Marshall, and J.F. Richard. 1997. "Bidder Collusion at Forest Service Timber Sales." *Journal of Political Economy* 105: 657-699.

Banerji, A., and J.V. Meenakshi. 2004. "Buyer Collusion and Efficiency of Government Intervention in Wheat Markets in Northern India: An Asymmetric Structural Auctions Analysis." *American Journal Agricultural Economics* 86: 236-253.

Bourgeon, J-M., and Y. Le Roux. 2001. "Traders' Bidding Strategies on European Grain Export Refunds: An Analysis with Affiliated Signals." *American Journal of Agricultural Economics* 83: 563-575.

Bourgeon, J-M., and Y. Le Roux. 1996 "Tenders for European Cereal Export Refunds: A Structural Approach." *European Review of Agricultural Economics* 23: 5-26.

Bresnahan, T.F. 1989. *Industries with Market Power*. Handbook of Industrial Organization. R. Schmalensee and R. Willing (eds.), North Holland, Amsterdam.

Christie, W.G., and P.H Schultz. 1994. "Why Do NASDAQ Market Makers Avoid Odd Eighth Quotes?" *Journal of Finance* 49: 1813-1840.

Crespi, J., and R.J. Sexton. 2004. "Bidding for Cattle in the Texas Panhandle." *American Journal of Agricultural Economics* 86: 660-674.

DiNardo, J., and J. Tobias. 2001. "Nonparametric Density and Regression Estimation." *Journal of Economic Perspectives* 15: 11-28.

Guerre, E., I. Perrigne, and Q. Vuong. 2000. "Optimal Nonparametric Estimation of First-Price Auctions. *Econometrica* 68: 525-574.

Härdle, W., M Müller, S. Sperlich, and A. Werwatz. 2004. *Nonparametric and Semiparametric Models*. Springer-Verlag, Berlin, Heidelberg.

Hogan, R.J.Jr., C.E. Ward, J.N. Trapp, D.S. Peel, and S.R. Koontz. 2003. *Economic Components of the Fed Cattle Market Simulator*. Oklahoma Agricultural Experiment Station, Research Bulletin B-817.

Hortaçsu, A. 2002. "Mechanism Choice and Strategic Bidding in Divisible Good Auctions: An Empirical Analysis of the Turkish Treasury Auction Market." Working Paper, University of Chicago. Available at http://home.uchicago.edu/~hortacsu/paper2_aug2.pdf, Accessed on May 12, 2006.

Klemperer, P. 1999. "Auction Theory: A Guide to the Literature." *Journal of Economic Surveys* 13: 227-286.

Koontz, S., and P. Garcia. 1997. "Meat-Packer Conduct in Fed Cattle Pricing: Multiple-Market Oligopsony Power." *Journal of Agricultural and Resource Economics* 22: 78–86.

Krishna, V. 2002. *Auction Theory*. Elsevier Science, Academic Press. San Diego, California.

Laffont, J.J., and Q. Vuong. 1996. "Structural Analysis of Auction Data." *The American Economic Review* 86:414-420.

Lopez, A.L., A.M. Azzam, and C.L-Espana. 2002. "Market Power and/or Efficiency: A Structural Approach." *Review of Industrial Organization* 20: 115-126.

McAfee, R. P., and J. McMillan. 1992. "Bidding Rings." *The American Economic Review* 82: 597-599.

Meyer, D.J. 1988. "Competition and Bidding Behavior: Some Evidence from the Rice Market." *Economic Inquiry* 26: 123-131.

Milgrom, P.R., and R.J. Weber. 1982. "A Theory of Auctions and Competitive Bidding." *Econometrica* 50:1089-1122.

Paarsh, H.J. 1992. "Deciding between the Common and Private Value Paradigms in Empirical Models of Auctions." *Journal of Econometrics* 51:191-215.

Paul, C.J.M. 2001. "Market and Cost Structure in the U.S. Beef Packing Industry: A Plant-Level Analysis." *American Journal of Agricultural Economics* 83: 64-76.

Porter, R. H., and J.D. Zona. 1993. "Detection of Bid Rigging in Procurement Auctions." *Journal of Political Economy* 101: 518-538.

Porter, R. H., and J.D. Zona. 1999. "Ohio School Milk Markets: An Analysis of Bidding." *Rand Journal of Economics* 30: 263-288.

SAS Institute. 2002-2003. SAS System Under Microsoft Windows. Release 9.1. SAS Institute Inc., Cary, North Carolina.

Sexton, R.J. 2000. "Industrialization and Consolidation in the US Food Sector: Implications for Competition and Welfare." *American Journal Agricultural Economics* 82: 1087-1104.

Schroeter, J. R. 1988 "Estimating the Degree of Market Power in the Beef Packing Industry." *The Review of Economics and Statistics* 70:158-162.

Sheather, S. J. 2004. "Density Estimation." *Statistical Science* 19: 588-597.

Ward, C.E. 1982. "Relationship between Fed Market Cattle Shares and Price Paid by Beefpackers in Localized Markets." *Western Journal of Agricultural Economics* 7:179-186.

Ward, C.E. 1992. "Inter-Firm Differences in Fed Cattle Prices in the Southern Plains" *American Journal of Agricultural Economics* 74:480-485.

Ward, C.E. 2002. "A Review of Causes for and Consequences of Economic Concentration in the U.S. Meatpacking Industry." *Current Agriculture, Food & Resource Issues* 3: 1-28.

Ward, C.E. 2005. "Price Discovery and Pricing Choice Under Divergent Supply Scenarios in an Experimental Market for Fed Cattle." *Journal of Agricultural and Resource Economics* 30: 580-596.

Ward, C.E., and T.C. Schroeder. 2001. *Understanding Livestock Pricing Issues*. Oklahoma Cooperative Extension Service, Division of Agricultural Sciences and Natural Resources, Oklahoma State University, F-551.

Zellner, A., and H. Theil. 1962. "Three-Stage Least Squares: Simultaneous Estimation of Simultaneous Relations." *Econometrica* 30: 54-78.

Table 1. Mean and Standard Deviation of the Variables from the Experimental Market

Variable	Mean	S D
	Before Merger (n=302)	
ADRWT (cwt)	721.6	1.7
ADRPRC ($/cwt)	128.8	0.5
BBPRC ($/cwt)	125.3	2.5
SHWLST (pens)	113.4	4.2
TODEM (pens)	38.3	4.4
HHI	0.3	0.009
	After Merger (n=290)	
ADRWT (cwt)	723.6	2.2
ADRPRC ($/cwt)	118.7	1.9
BBPRC ($/cwt)	121.7	2.8
SHWLST (pens)	131.2	8.8
TODEM (pens)	41.7	3.5
HHI	0.5	0.01

Table 2. Maximum Likelihood Parameter Estimates and Standard Errors of the Nonnested Model

Parameter	Estimate	Standard error	t-value	Pr > |t|
intercept	-10.80	8.25	-1.31	0.2086
cattle inventory (*shwlst*)	-0.01	0.07	-0.08	0.9343
total demand (*todem*)	0.13	0.12	1.04	0.3129
cattle from Feedlot 1 (*fdlt*1)	0.17	0.19	0.87	0.3979
cattle from Feedlot 2 (*fdlt*2)	-0.06	0.20	-0.32	0.7522
cattle from Feedlot 3 (*fdlt*3)	-0.59	0.19	-3.05	0.0076
cattle from Feedlot 4 (*fdlt*4)	0.24	0.19	1.22	0.2401
cattle from Feedlot 5 (*fdlt*5)	-0.83	0.20	-4.22	0.0006
cattle from Feedlot 6 (*fdlt*6)	-0.41	0.20	-2.05	0.0575
cattle from Feedlot 7 (*fdlt*7)	0.44	0.21	2.1	0.0515
medium generic carcass (*GenM*)	1.25	0.12	10.82	< 0.0001
high generic carcass (*GenH*)	3.03	0.13	22.7	< 0.0001
cattle sold at 1500 lbs. (*wt*150)	1.07	0.19	5.74	< 0.0001
cattle sold at 1500 lbs. (*wt*175)	3.92	0.31	12.62	< 0.0001
Herfindahl index (*HHI*)	11.95	6.04	1.98	0.0654
indicator for bidder 1 (*bidder*1)	0.47	0.44	1.06	0.3053
indicator for bidder 2 (*bidder*2)	0.38	0.22	1.78	0.0947
indicator for bidder 3 (*bidder*3)	0.28	0.15	1.86	0.0811
intercept of the variance equation	0.44	0.87	0.51	0.619
slope of inventory in the variance equation	-0.02	0.01	-2.55	0.0215
slope of total demand in the variance equation	0.05	0.01	3.32	0.0043
variance of time random effect	4.38	1.52	2.88	0.011
-2 log-likelihood	1916.6			

Table 3. Structural Auction Estimates of Cattle Price Markups

Packer	Price markdown	Interquartile range	Herfindahl index
before merger (optimal bandwidth = 0.36)			
packer 1	1.06	1.15	
packer 2	1.33	0.78	
packer 3	2.77	0.81	
packer 4	2.41	1.12	
all four packers	2.00	0.91	0.264
after merger (optimal bandwidth = 0.69)			
Packers 1&2	5.78	1.10	
Packers 3&4	3.89	2.26	
all two packers	4.71	1.54	0.512
Industry (before & after mergers)			

Note: Optimal bandwidths of 0.28 before merger and 0.81 after were selected using Sheather-Jones plug in method.

Table 4. Nonlinear Two-Stage Least Squares Estimates of the NEIO Model

Parameter	Symbol	Estimate	Standard error	p-value
Industry conjectural variation	Θ	-0.94	0.19	0.0004
Processor's pricing equation intercept	a_0	-4.76	2.31	0.0633
Coefficient for packer's marginal cost	a_1	13.06	34.04	0.7085
Price markdown		2.7		