A Multinomial Logit Framework to Estimating Bid Shading in Procurement Auctions, With Application to Cattle Sales in the Texas Panhandle

John M. Crespi
Kansas State University

Richard J. Sexton
University of California, Davis

Abstract: Many auctions have complicated and idiosyncratic features that, individually or in combination, make structural analysis difficult or impossible. In these more complicated auction settings, theory may only provide heuristic guidance as to the factors that determine equilibrium bids and the selling or acquisition price of the item(s) being auctioned. In this paper, we develop an empirical model to estimate the magnitude of bid shading present in an auction based upon multinomial probability models. The methodology works well in settings where data allow a good estimation of a bidder's probability of winning, but the approach doesn't rely upon the bidding process following any particular structural framework or on the existence of a control group. We apply the model to bidding for live cattle by beef-packing plants in the Panhandle region of Texas, where idiosyncratic features of the bidding environment make structural analysis difficult or impossible.

Funding for this study was provided by the USDA Economic Research Service (ERS), and some of the data were provided by the USDA Grain Inspection, Packers and Stockyards Administration (GIPSA). The views and opinions expressed in the paper do not necessarily reflect the views of ERS, GIPSA, or USDA. The authors are grateful to Ted Schroeder and Rodney Jones for helpful discussions.

A Multinomial Logit Framework to Estimating Bid Shading in Procurement Auctions, With Application to Cattle Sales in the Texas Panhandle

I. Introduction

Considerable progress has been made in empirical analysis of auctions that have been designed around a particular structural format (e.g., government telecommunications auctions (*The Economist* [1997])), or can be assumed to fit a familiar structural format (e.g., Laffont, Ossard, and Vuong [1995], Baldwin, Marshall, and Richard [1997]). However, many auctions in the real world have complicated and idiosyncratic features that, individually or in combination, make structural analysis difficult or impossible. Prominent examples include sequential auctions where multiple units of a product are sold over time, auctions with multiple, competing sellers, or auctions that feature irrational bidders (Goeree, Holt, and Palfrey [2002]), asymmetric bidders (Campo, Perrigne, and Vuong [2003]), risk-averse bidders (Campo, Perrigne, and Vuong [2002]), and bidders who may collude (Graham and Marshall [1987]). In these more complicated auction settings, theory may only provide heuristic guidance as to the factors that determine equilibrium bids and the selling or acquisition price of the item(s) being auctioned.

An important policy question for many instances is the "competitiveness" of the auction in the sense of its ability to generate maximum revenues for a seller or minimum costs for a buyer in the case of a procurement auction.[1] To date, the competitiveness of bidding has been evaluated in two ways: (a) by comparing the behavior of known or suspected colluding bidders with a control group of competitive bidders (Porter and Zona [1993, 1999] and Pesendorfer [2000]), or, if the auction fits or can be assumed to fit a standard structure, by recovering bidders' valuations from observed bidding behavior (Monier-Dilhan and Ossard [1998]). These approaches, while valuable, are limited in application because many auctions lack an adequate

[1] For example, Blair and Kaserman [1993, pp. 4-7] motivate their treatise on monopsony with several examples from procurement auctions (see the references they cite for specific examples).

descriptive structural model due to their complexity and no competitive control group of bidders can be identified.[2] Recently, Bajari and Ye [2003] have developed tests to detect collusive behavior that do not rely upon identifying a control group of noncolluding firms.

This paper presents an alternative framework for evaluating the competitiveness of an auction. We develop an empirical model to estimate the magnitude of bid shading present in an auction based upon simple probability estimations. The methodology works well in settings where data allow a good estimation of a bidder's probability of winning, but the approach doesn't rely upon the bidding process following any particular structural framework or on the existence of a control group. We apply the model to bidding for live cattle by beef-packing plants in the Panhandle region of Texas, where idiosyncratic features of the bidding environment make structural analysis difficult or impossible. Another rather unique feature of our application is that we lack data on losing bids and, in fact, don't even know how many bids were received on the lots of cattle in our data set. We argue that, outside the realm of the sealed-bid government procurement auctions that have been the subject of most prior empirical investigations of behavior in auctions, this data limitation will be relatively common, making methods that can proceed without such data of considerable interest.

The competitiveness of livestock procurement in the U.S. has been a subject of frequent economic analysis and fierce policy debate. Surveys by Azzam and Anderson [1996] and Ward [2002] summarize much of the economic analysis. On balance, this research suggests a disconnect between the angst expressed by many producers and policy makers as to the consequences of the dramatic structural evolution of the industry, and the industry's actual

[2] On this point, both the Porter and Zona [1993, 1999] and Pesendorfer [2000] studies relied on antitrust prosecutions to distinguish competitive bidders from those suspected of collusion.

performance.[3] Azzam and Anderson opine "that the body of empirical evidence . . . is not persuasive enough to conclude that the industry is not competitive" (p. 124). Ward's read of the empirical evidence suggests to him that price distortions from imperfect competition in meatpacking are on the order of three percent or less. Azzam [1997] and Morrison-Paul [2001] concluded that the positive efficiency aspects of packer consolidation dominated small, negative impacts due to packer market power.

Producer groups and policy makers, however, have continued to express concerns about the competitiveness of cattle procurement in the U.S. (McEowen, Carstensen and Harl [2002], Rogers [2002]). The U.S. Senate Judiciary Committee held hearings in August 2002 on the impacts of increasing consolidation in meatpacking on producers and consumers, and Senator Tom Daschle and others have called for greater antitrust enforcement in the industry (Pore [2002]). Pending legislation in the U.S. Congress would ban most packer ownership of cattle, and, as well, a number of private lawsuits have been filed and are pending under Federal or state antitrust statutes.

Most prior empirical work on competition issues in the cattle/beef industry has relied upon aggregate time-series data and utilized either the reduced-form approach of the structure-conduct-performance paradigm or various structural frameworks associated with the new empirical industrial organization (NEIO). Either approach has faced the daunting task of

[3] Development of the "boxed-beef" packing technology in the late 1970s induced important efficiency gains and significant economies of scale in the processing sector. At the same time, the U.S. experienced declining demand for red meats, with per capita consumption falling from 95 lbs. in 1976 to the mid 60 lb. range during the 1990s (Purcell [2000]). These factors led to rapid consolidation in the packing sector. A relatively unconcentrated industry, with four-firm concentration (CR4) in the range of 25% in 1976 quickly became a rather tight structural oligopoly/oligopsony with CR4 = 80% in 1998 (USDA [1998], Ward [2002]).

isolating the influences of dramatic changes in demand, processing technology, concentration, and marketing arrangements on key performance variables.[4]

Researchers have seldom taken the bidding processes in cattle procurement into account. Those who have attempted to address the uncertainty inherent in markets that include bidding, have not investigated the structure of the auction or the probabilities of buyers obtaining particular lots of cattle, but rather have sought to measure the effects of industry structure variables, such as concentration ratios, number of bidders, or usage of vertical contracting, on prices bid (e.g., Ward [1981, 1982, 1992], Schroeder et al. [1993]). Although various papers in the NEIO framework have utilized bid data, none have taken the probabilistic nature of the bidding environment into account when analyzing competition in the market. Rather, firms have been modeled as being able to purchase supplies as needed, according to a known producer supply curve. As such, unlike the present study, these models do not incorporate the reality that a firm's bid affects only its probability of obtaining supplies in livestock markets.

II. Economic Analysis of Auctions

Because they often represent stylized markets with well-defined rules, some auctions have proven to be quite amenable to analysis using the tools of noncooperative game theory. Common features among the auctions analyzed in theory are a monopoly seller or a monopsony buyer (e.g., a government soliciting bids on a project) and asymmetry of information among participants (Klemperer [1999]). Unlike standard models where quantities are presumed certain for given prices, a model of a procurement auction must reflect that a player's probability of winning is a function of the amount bid. Further, the buyer's profit margin is inversely related to the amount bid. Thus, the optimal noncooperative bidding strategy must balance this tradeoff

[4] See Azzam and Anderson [1996], Sexton [2000], and Ward [2002] for more extended critiques of the extant empirical work.

and, in general, will depend upon (a) the form of the auction, (b) the player's valuation of the item(s) being auctioned, (c) the number of players bidding in the auction, (d) the seller's reservation price, if any, and (e) the players' knowledge regarding other bidders' valuations, such as the distribution function from which the valuations are drawn.

The optimal noncooperative bidding strategies have been derived for particular auction settings. A prominent and oft-analyzed example is the first-price auction with independent, symmetric, private values. The Bayesian Nash equilibrium for this format was derived by Riley and Samuelson [1981] (see also the references in Klemperer [1999]), and an estimation framework has been developed in work by Laffont, Ossard, and Vuong [1995] and Guerre, Perrigne, and Vuong [2000]. However, as noted, a great number of factors complicate bidding in many real-world settings. In these generalized auction settings, theory can provide only heuristic guidance as to the factors that determine equilibrium bids, and, hence, to empirical estimation of the existence and extent of bid shading in the auction.

Prior empirical analyses of auction settings can be classified into three loose categories: structural econometric modeling of auctions that are assumed to fit one of the standard paradigms (Paarsch [1992], Laffont, Ossard, and Vuong [1995] and Monier-Dilhan and Ossard [1998]), tests of various predictions emanating from the economic theory of auctions,[5] and tests for competition or collusion in auctions. Of the latter, key papers include Porter and Zona for highway paving jobs in New York [1993] and school milk contracts in Ohio [1999], Baldwin, Marshall, and Richard [1997] for forest timber sales, Pesendorfer [2000] for school milk contracts in Florida and Texas, and Garcia-Diaz and Marin [2003] for electricity markets in Spain.

[5] This work is best exemplified by several studies by Hendricks and Porter focusing on U.S. auctions for oil and gas leases. Porter [1995] provides a review of this work.

III. A Model to Estimate Bid Shading

Our goal is to derive an empirical model that enables estimation of the difference between a bidder's valuation and the price bid for generalized bidding environments when (a) recovering bidders' valuations from the bid data using the structural methods (e.g., Laffont, Ossard, and Vuong [1995] or Guerre, Perrigne, and Vuong [2000]) is not possible, given the complexity of the bidding process, and (b) valuations cannot be inferred from data on bidders' costs or from a control group of bidders who can be assumed to be acting competitively (e.g., as in Porter and Zona [1999]. Although the model applies rather generally, for concreteness we develop the exposition in the context of our application to feedlots selling cattle to beef-packer buyers.

III(i). The Bidding Model

We assume that packer i sets W_i^f to maximize its expected profit on a lot transaction.[6] As noted, uncertainty unavoidably arises as a consequence of the bidding process, making this problem different from a classical oligopsony or monopsony model where a firm is assumed to face a given supply. Specifically, an individual packer's supply of spot-market cattle from a particular feedlot is

$$S_i^f = \rho_i^f Q^f + \eta_i^f, \tag{1}$$

where Q^f is the quantity available in the lot, and η_i^f is an unobserved, mean zero, stochastic component. As such, packer i's expected supply from feedlot f at any given time is

$$ES_i^f = \rho_i^f Q^f. \tag{2}$$

In this model the packer's bid affects the supply by affecting packer i's probability of obtaining animals from feedlot f, ρ_i^f. Thus, supply is positively related to the bid,

[6] The assumption of packer profit maximization at the individual transaction level is supported by heuristic evidence. Packers compute earnings for each lot of cattle they procure, and their agents, the buyers in the field, are evaluated on the profitability of the lots they procure.

$\partial S_i^f / \partial W_i^f = [\partial \rho_i^f / \partial W_i^f] Q^f > 0$, reflecting the fact that in order to increase its probability of obtaining cattle from feedlot f, the packer must raise its bid. Conversely, packer i's supply is negatively related to a rival's bid, $\partial S_i^f / \partial W_j^f = [\partial \rho_i^f / \partial W_j^f] Q^f < 0$, and the packer determines a bid, W_i^f, for a lot in order to maximize its expected profit on that lot given by

(3) $$E\pi_i^f = (P^f - W_i^f - c_i) ES_i^f - A_i^f ,$$

where c_i is a per-unit, packer-specific marketing cost and $A_i^f \geq 0$ is the fixed cost associated with the transaction, which may or may not be lot specific. Note that the wholesale price for the processed product, P^f, can differ by feedlot transaction because the quality characteristics of the processed beef will differ among those lots, but we assume a competitive market for the processed product so that P^f is exogenous.[7]

The first-order condition for equation (3) is

(4) $$\partial E\pi_i^f / \partial W_i^f = (P^f - W_i^f - c_i)(\partial ES_i^f / \partial W_i^f) - ES_i^f = 0 .$$

Rewriting this condition gives,

(4') $$(P^f - W_i^f - c_i)(\partial \rho_i^f / \partial W_i^f) Q^f - \rho_i^f Q^f = 0 .$$

Define $\partial \rho_i^f / \partial W_i^f \equiv \varpi_i^f$, and assume that $\varpi_i^f > 0$. Rearranging (4') yields:

(5) $$P^f - c_i - W_i^f = \rho_i^f / \varpi_i^f .$$

Packer i knows that the feedlot owner will sell the cattle to whichever packer offers the best deal, i.e., letting $\varphi_i^f \equiv \varphi_i^f(W_i^f)$ denote the profit to feedlot f from selling to packer i, a feedlot will choose packer i over packer j whenever $\varphi_i^f > \varphi_j^f$. A packer cannot perfectly observe the feedlot's profit from either its or its rival's bids. However, we assume that the packer can

[7] This assumption can be motivated readily by noting that selling markets for processed boxed beef are national or international in geographic scope, while procurement markets are local or regional.

estimate a feedlot's profit on a lot in terms of a set of internal and market variables that jointly determine profit.

For any given transaction, the feedlot owner's random profit from choosing to accept packer i's bid can be written as

(6) $$\varphi_i^f = \alpha W_i^f + \boldsymbol{\gamma}' \mathbf{K_i^f} + \varepsilon_i^f .$$

Here α is a parameter and $\boldsymbol{\gamma}$ is a parameter vector, each to be estimated, $\mathbf{K_i^f}$ is a vector of explanatory variables composed of feedlot costs and a lot characteristic vector $\mathbf{V^f}$, and ε_i^f is an error term that is assumed to follow a Weibull distribution--see the discussion in Greene [2000, p. 858]. Let Y^f be a random variable indicating the choice that feedlot f makes among the N packers. Under such conditions (McFadden [1973]), the probability that feedlot f chooses packer i, ρ_i^f = Prob(Y^f = i), can be determined from estimation of the following multinomial logit (MNL) model:[8]

(7) $$\rho_i^f = \frac{\exp[\alpha W_i^f + \boldsymbol{\gamma}'\mathbf{K_i^f}]}{\sum_{j=1}^{N}\exp[\alpha W_j^f + \boldsymbol{\gamma}'\mathbf{K_j^f}]} .$$

From the MNL estimation, we can obtain estimates at each transaction for ρ_i^f and ϖ_i^f. Thus, equation (5) can be calculated at each transaction to obtain an estimate of $P^f - c_i - W_i^f$. The term ρ_i^f / ϖ_i^f in (5) is the markdown of the bid, W_i^f, relative to the bidder's valuation of the lot, $P^f - c_i$ i.e., ρ_i^f / ϖ_i^f is the estimate of bid shading.[9]

---

[8] This particular type of multinomial logit model is also commonly called a "conditional logit" model. See Greene [2000, p. 862].

[9] For example, in the case of a first-price auction with independent private values and symmetric bidders without the idiosyncrasies we discuss with respect to live cattle bidding, the analytical model of bid-shading with *N* buyers and a reservation price of W_o is known to be $W_i(x) = x - \int_{W_o}^{x} F^{N-1}(y)dy / F^{N-1}(x)$ for packer i with valuation *x* distributed

The larger the value of ϖ_i^f, the more responsive is the probability of winning to the magnitude of the bid and, hence, the more competitive is the auction. On the other hand, if a market allocation scheme were in place, then ϖ_i^f would be small because the allocation of cattle is being decided on a basis other than the strength of the bid.[10] We ordinarily do not know the individual price and cost components, P^f or c_i, because the information simply does not exist or is confidential. However, the utility of this model is that it allows us to estimate bid shading via a Lerner index, Λ_i^f, without having to derive an analytical model for an auction format that may be very complex and analytically intractable. Moreover, we have none of the usual problems of aggregation or averaging, as are common in many NEIO models. In this case, we are able to obtain a Lerner index for every transaction and every packer, namely,

$$(8) \qquad \Lambda_i^f = (P^f - c_i - W_i^f)/(P^f - c_i) = (\rho_i^f/\varpi_i^f)/[(\rho_i^f/\varpi_i^f) + W_i^f].$$

Further, we can examine what happens to markdowns as a function of the characteristics of the items being auction, for example the distance a feedlot is located from a packer, or the quality characteristics of the animals in the lot.

III(ii). Accounting for the Losing Bids

The data set for our application, as well as many others, lacks one necessary piece of information to implement the model derived here, namely the value of the losing bids. Although losing bids are sometimes available, as in the case of sealed bids solicited by public agencies (e.g., Porter and Zona [1993, 1999]), the more likely case is that they are unavailable. For example, no record of unsuccessful bids is normally recorded from an open outcry (English) auction, and a descending (Dutch) auction reveals no evidence of losing bids because, by design of the auction,

---

over some cumulative distribution function, *F* (see Riley and Samuelson [1981, p. 385]). In this case, the bid shading in (5) would correspond with the term to the right of the minus sign if we define $x = P^f - c_i$.

[10] The appendix to this paper shows a complementary interpretation.

the losing bids are not revealed. Finally, as we discuss in more detail below, although the cattle auctions we study are of the sealed bid variety and reporting of sales prices (i.e., winning bids) is nowadays required by law, no reporting is required for losing bids and such data, if it is retained at all, would be confidential.

However, if the data set on winning bids is sufficiently rich in number of observations and on the characteristics of the items for auction, it may be possible to recover the losing bids using a censored regression model. For example, in our application we know the price that was paid for all of the lots of cattle in the data set, and we can assume that the losing bids were below this price. Thus, we can use the winning bid as a censoring point for bids by packers who did not receive the cattle. This approach, however, is not without limitations. First, the technique described here presumes that all of the packers in the data set made a bid on each of the lots, although ample heuristic evidence suggests that feedlots often received only one or two bids on a lot. However, even when a packer did not actually bid on a lot, it arguably had a reservation price on the lot. Thus, the predicted losing bid in this case can also be viewed as a reservation price.

A second limitation is related. If in fact there were an allocation scheme (tacit or otherwise) among the bidders, then we should expect that low bids would not be derived from the same distribution as winning bids (Porter and Zona [1993, 1999]). For example, if the beef packers were colluding, then some proportion of losing bids may be "junk" bids, submitted by a packer without expectation of winning. However, assuming, as we do, that losing bids are drawn from the same distribution as winning bids and that all packers in the data set participate in the bidding biases the analysis in favor of less bid shading and more competition among bidders, and, thus, to the extent these assumptions do not hold, their presence lends a degree of conservatism to the analysis.[11]

Specifically, we want to know the bid on lot f by packer i, W_i^f, regardless of whether that bid was the winning or losing bid. However, we only observe the price offered by packer i when i has the winning bid on lot f. For winning bids by packer j, however, we assume that $W_i^f < W_j^f$. In other words, our observation of packer i's bid is censored at W_j^f in that case. We assume that a bid by packer i is determined by a vector of lot and packer characteristics, X_i^f, such that $W_i^f = \boldsymbol{\beta}_i^{'}\mathbf{X}_i^f + \varepsilon_i^f$. Further, assuming that $\varepsilon_i^f \sim N[0,\sigma_i^2]$, then our observed, censored bid is

$$\tilde{W}_i^f \begin{cases} = W_i^f & \text{if} \quad W_i^f = \max\{W_1^f,\ldots,W_N^f\} \\ < W_j^f & \text{if} \quad W_j^f = \max\{W_1^f,\ldots,W_N^f\},\ j \neq i \end{cases}.$$

It can be shown that the expected value and variance of the censored bid are given by $E[\tilde{W}_i^f] = \Phi W_j^f + (1-\Phi)(\beta_i^{'}x_i^f + \sigma_i\lambda)$ and $Var[\tilde{W}_i^f] = \sigma_i^2(1-\Phi)\{(1-\delta) + [(W_j^f - \beta_i^{'}x_i^f)/\sigma_i - \lambda]^2\Phi\}$, where $\Phi = Prob(W_i^f \leq W_j^f)$, ϕ is the normal density function, $\lambda = \phi/(1-\Phi)$, and $\delta = \lambda^2 - \lambda(W_j^f - \beta_i^{'}x_i^f)/\sigma_i$. From this specification, we can estimate the vector of parameters $\hat{\boldsymbol{\beta}}_i$ for each packer (Greene [2000, pp. 905-911]) that will allow us to derive a value for all bids, $\hat{W}_i^f$, such that

(9)
$$\hat{W}_i^f = \begin{cases} W_i^f & \text{if} \quad W_i^f = \max\{W_1^f,\ldots,W_n^f\} \\ \hat{\boldsymbol{\beta}}_i^{'}\mathbf{X}_i^f & \text{if} \quad W_j^f = \max\{W_1^f,\ldots,W_n^f\},\ j \neq i \end{cases}.$$

[11] In other words, if a bidder has no intention of winning certain lots and offers "junk" low bids in order to aid a rival, then we should expect these low bids to be drawn from a distribution with a lower average than that of the winning bids. As the discussion of the censored bid construction below will show, our assumption that the losing bids are valid bids, i.e., drawn from the same distribution as the winning bids, will cause the prediction of the losing bids to be higher on average than the case in which the bidders rationally submitted "junk" low bids.

IV. Application to Cattle Procurement in the Texas Panhandle

The Panhandle, a plains region consisting of the northern tip of Texas, is one of the most intensive areas of cattle feeding in the U.S. It is home to four large processing plants that accounted jointly for 90% of the slaughter of steers and heifers in Texas and 17% of the U.S. slaughter during our Feb. 1995 – May 1996 study period. Two of the plants, one in Friona and one in Plainview, are owned by Excel Corp (a division of Cargill), an IBP, Inc. plant is located in Amarillo (IBP was acquired by Tyson Foods in 2001), and Swift & Co. operates a plant in Dumas. Prior to 2002, this plant was operated by Monfort, Inc., a division of ConAgra. During the sample period, the combined average daily slaughter for these four plants was 15,730 head. IBP, ConAgra, and Excel are also the three largest beef processors nationally. In 1999, IBP had an estimated daily slaughter capacity of 38,800 head, followed by ConAgra and Excel with daily capacities of 23,000 and 22,500 head, respectively (Ward and Schroeder [2000]).

The region is also home to many large feedlots. Over 300 feedlots sold cattle to the Panhandle-region packers during the February 1995 – May 1996 study period. Although the Panhandle packers procure cattle from a broad area that includes Oklahoma, southern Kansas, New Mexico, and Arizona, the vast majority of cattle are procured within the Panhandle region itself. Among the approximately 6.2 million head slaughtered by the four plants during the sample period, 65.5% were procured within a 75-mile radius of the packing plant, and another 26.5% were procured within a 76-150 mile radius. Approximately 70% of these cattle were acquired through spot transactions and 26% through exclusive marketing agreements,[12] with the

[12] Marketing agreements are contracts that commit a producer to sell to a particular packer. Pricing in these arrangements is usually based upon a formula, with a base price that is often tied to the cash-market price and various premia and discounts for quality factors. Marketing agreements differ from forward contracts in that the latter are usually not exclusive selling arrangements, and price is often based on a futures contract.

rest procured either through forward contracts or packer ownership. Our focus is exclusively on the spot-market purchases.

The procurement process for spot-market cattle in the region resembles a form of first-price, sealed-bid auction. Feedlot operators provide show lists of lots of cattle available for sale during each week. Packer representatives may inspect these cattle and submit bids, usually by phone or fax. Bids are generally valid for the day in which they were tendered. The bids are "sealed" from an auction theory perspective because the packers do not know with certainty which of their rivals has bid on the various lots and at what price. However, the packers may acquire very good information on others' bids through reported sales prices and information provided by feedlot owners. Feedlot operators may elect not to accept any of the tendered bids, in which case bidding on those lots begins anew on the following day. The seller's opportunity to refuse any and all bids implies the existence of reservation prices, but the reservation prices are not announced and may vary over time for lots that are listed for sale on multiple days and among lots on the same show list. If a bid is accepted, the packer pays his bid price (i.e., the first-price feature) and arranges for delivery to the packinghouse, which usually occurs within seven days.

The general and analytically intractable case of asymmetric bidders and affiliated valuations would appear to apply to cattle procurement auctions in the Panhandle region. Because both packers and feedlots are distributed spatially and packers generally incur the shipping costs, the geographic location of a lot will cause its value to differ among the processors. Packers may also differ in their valuations of the quality characteristics of a lot, depending upon the finished products each is seeking to produce. Each plant produces boxed beef for sale to wholesalers and/or retailers. At the time they bid to acquire cattle for processing, the packers do not know with certainty the value of the finished, boxed-beef product, but they observe a similar set of market signals that combine to determine this value, thus leading to affiliated valuations.

The procurement auctions in the Panhandle have various other idiosyncratic features that distinguish them from prototype auctions. A queuing convention has emerged whereby the first bidder on a lot of cattle is said to be "on the cattle" and is given an opportunity to revise his bid in the event that someone bids a higher price. The optimal bidding strategies in the presence of this convention no doubt differ from what would be optimal in its absence. Another convention is that usually packers bid only whole dollar amounts per hundred lbs. of weight (cwt), enhancing the likelihood that identical bids will be received, in which case, if a bid is accepted, the cattle go to the buyer who is first in the queue. Eighty percent of the transactions in our data set were in whole dollar amounts per cwt. This whole-dollar bidding feature contributes to bid shading in and of itself because a rational bidder will never bid above his valuation of a lot. Thus, bids will always be rounded down. For example, a bidder who valued a lot at $70.75 per cwt would bid at most $70.00 per cwt under whole-dollar bidding.[13]

In addition to this evidence that the bidding process seems ill suited to advance sellers' interests, various other features of the market environment raise concerns about its competitiveness and the possibilities for collusive behavior among bidders. Prominent among them, of course, is that only four plants and three firms operate in the region. Although sales to outside firms are possible, those sales incur higher costs due to longer hauls.[14] In the cash market, packers compete mainly based upon price, i.e., non-price considerations, such as

[13] Shading due to bidding agreements like the whole-dollar convention here have been studied in other markets; see, for example, Christie and Shultz' study of collusion and odd-eighth bids on the NASDAQ market.

[14] The main source of potential outside competition would appear to be Farmland National Beef Packing Co., the fourth largest beef processor nationally, with daily slaughter capacity of 9,000 head. Farmland operates two plants in southwestern Kansas (Ward and Schroeder [2000]).

timeliness of payment or services provided by the buyer, are of minor importance, thus implying little "product differentiation" among the buyers and making coordination among them easier (Porter and Zona [1993, 1999]).

Cattle sales during the study period were subject to voluntary price reporting to the U.S. Department of Agriculture (USDA) Market News Service. (Mandatory price reporting was implemented in 2001.) Thus, although bids were sealed nominally, selling prices were often available on short notice through Market News or private industry sources. Because packers tend to bid identical prices for similar lots, prices bid for unsold lots can probably be inferred with considerable accuracy from the reported sales prices. If an agreement regarding pricing were in place, public reporting of sales prices would enable firms to monitor compliance with the agreement.[15] Finally, the fact that the region contains many sellers, and sales take place repeatedly through time, makes it relatively easy to find allocations of the market that are mutually advantageous to the buyers (Pesendorfer [2000]). For example, there is no need for complicating factors such as side payments, as would be true if bidders were colluding over the sale of a single object.

IV(i). Data

The primary data set was collected by the USDA Grain Inspection, Packers, and Stockyards Administration. It contains information on every lot of cattle containing more than 35 head that was acquired by one of the four beef packing plants in the Panhandle region during the period from February 1995 to May 1996, 37,112 transactions in total. The transactions were categorized as either spot-market sales, marketing agreements, forward contracts, or packer-fed cattle. Although this geographic market has been studied previously and other authors have

[15] Interviews with feedlot managers in the Panhandle region conducted by the USDA generated some evidence that sellers were occasionally requested by buyers to not accurately report the transaction price.

utilized the same data set, none of the previous work has focused on the bidding aspect of the market and the probabilistic nature of supply.[16]

The estimation for this paper focuses only on the 24,425 spot-market transactions. Further, because any packer market power will be attenuated as the packers in the Panhandle region compete for lots that are located nearer to packers who are not in our data set (the nearest packers in southwestern Kansas, for example, are more than 200 miles from the center of the region in our study) and to increase the chance that the lots in our data set received bids from more than one packer, we focus on those feedlots within a 150-mile radius of the geographic center of the four packers. Thus, after accounting for possible errors in the data set, deleting observations with incomplete data, excluding cash-market cattle not sold on a live-weight basis, and focusing only on nearby cattle, we are left with 16,556 observations or roughly 68% of the spot-market transactions. The observations per plant ranged from 2,442 to 6,749.

Our use of the data set and reporting of results is governed by a nondisclosure agreement. Thus, we are unable to identify the plants, and refer to them instead as plants 1, 2, 3, and 4. Following CS [2003], we specified the following bid function for plants i = 1,2,3,4:[17]

---

[16] The data set has been analyzed by Schroeter and Azzam (SA) [1999, 2002a, 2002b], Hunnicutt, Bailey, and Crook (HBC) [2002], and Crespi and Sexton (CS) [2003]. The focus of SA's work is the relationship between packers' use of so-called "captive supplies" (i.e., cattle procured on a non-cash basis, including forward contracts, marketing agreements, and packer-owned cattle) and the spot or cash price and, accordingly, is quite different from our own. HBC examine issues of competition in the Panhandle, but they do not pursue the auction framework developed here, and their empirical methods differ considerably from our own. Finally, CS [2003] is a companion piece to the present work that analyzes a different set of questions from those at issue here. In particular CS [2003] focus on the fact that often only one or two packers bid on a given lot and ask what would happen to selling prices if each of the four plants in the region did bid on each available lot, given their bidding behavior as revealed by the lots each did acquire. CS [2003] do not investigate the competitiveness or degree of bid shading involved in that behavior.

[17] The regression models used are similar to the hedonic price functions estimated by SA [1999]. The main difference is the inclusion of a live cattle futures price and the boxed-beef price. These two variables were included in the hedonic pricing model estimated by Schroeder et al. [1993]. We also included a "nearest packer" variable (the distance from the feedlot to the nearest plant which did not obtain the cattle).

(10) $W_i = a_{0i} + a_{1i}BXPR + a_{2i}PRFUT + a_{3i}YIELD_i + a_{4i}HEAD_i + a_{5i}PCTYG13_i + a_{6i}PCTPC_i + a_{7i}MILES_i + a_{8i}AWS_i + a_{9i}AWS2_i + a_{10i}AWH_i + a_{11i}AWH2_i + a_{12i}AWM_i + a_{13i}AWM2_i + a_{14i}MON + a_{15i}TUE + a_{16i}WED + a_{17i}THU + a_{18i}FRI_i + a_{19i}NRST_i + a_{20i}NRST2_i + a_{21i}SUP_i + a_{22i}SUP2_i + a_{23i}SUPOTH_i + a_{24i}SUPOTH2_i + d_{1i}WEEK1 + \ldots + d_{66i}WEEK66 + \varepsilon_i$,

where ε_i is a random error term to account for the effect of factors excluded from the model.

Descriptions of these variables and summary statistics are contained in table 1. The variable BXPR is the wholesale boxed-beef price on the day the lot was sold, weighted for each lot based upon the percentage of beef in the lot grading prime/choice and select/other. PRFUT is the prior day's closing price on the Chicago Board of Trade for the futures contract nearest the sale date. PRFUT may reflect factors affecting the market for live cattle that are not fully reflected in the processed beef price.

Quality characteristics include the lot's YIELD (carcass weight divided by live weight), the number of HEAD in the lot, the percentage of the lot achieving yield grades 1, 2, or 3 (PCTYG13), the percentage of the lot grading prime or choice (PCTPC), and the distance in MILES the cattle were shipped to the processing plant. AWS, AWH, and AWM are the average carcass weight in the lot if the lot contains steers (S) (58% of lots), heifers (H) (37% of lots), or a gender mix (M), (5% of lots), respectively, and are zero otherwise. The squared values, MILES2, AWS2, AWH2, and AWM2 are also included to account for nonlinearities in the relationships.

NRST and its square account for the distance in miles from the selling feedlot to the nearest plant that did not procure the cattle and are included as measures of the intensity of spatial competition. To account for possible capacity constraints at the plants, we include a measure of previous purchases, SUP, defined as the moving average of number of head obtained by a packinghouse over the previous week. Seven days was chosen because that period represents the average time from purchase to slaughter in the data set. Relatedly, we also include SUPOTH, which measures the supplies purchased by competing plants over the prior seven days. This variable is included as a measure of dynamic interaction between a seller's bid and the supplies of its rivals. Finally, in keeping with the tradition of prior hedonic analyses of cattle prices (Ward [1992], Schroeder et al. [1993], SA [1999]), dummy variables (MON – FRI) are included for the day of the week the cattle were purchased (weekend purchases are the default), as are a series of dummy variables (WEEK1 – WEEK66) to reflect the week in which the lot was sold. The cattle market follows a well-known and oft-analyzed cycle (e.g., Rosen, Murphy, and Scheinkman [1994]), and the weekly dummy variables represent a simple way to account for dynamic considerations affecting the market. The rationale for day-of-week effects is less clear, although some industry participants claim that the market is "soft" at the beginning of a week and then tends to pick up later in the week.

Table 2 presents the results of estimating (10) using the censored regression model for each of the four plants. Estimation results for the 66 weekly dummy variables are not reported. Standard errors adjusted for the censoring appear in parentheses below the coefficient values. Most coefficients carry the expected signs and are significant at a 5 percent hypothesis-test level, although a few anomalies are apparent. One would expect the number of head in a lot and the degree of quality of cattle in the lot to have a positive relationship with the bid, while the distance to the nearest plant and magnitude of prior commitments should have a negative relationship. However, the signs of the coefficients on HEAD, PCTYG13, MILES, NRST, and SUP are mixed among the four plants. Because we have restricted the data set to only include feedlots in close proximity to the packers, the MILES and NRST variables may be serving as proxies for other information. After all, these variables are particular to a given feedlot's distance to the plants and may be picking up information such as the relationship that a particular feedlot has with a particular plant.

Actual winning bids averaged \$64.54 and ranged from \$50 to \$76 per cwt. By contrast, the deduced losing bids averaged approximately \$62.86 and ranged from \$20.42 to \$75.52 per cwt. A better comparison with the average winning bid, however, might be the predicted 2nd highest bid, which averaged \$63.42 per cwt. Although the log-likelihood is provided in table 2, measures of overall goodness of fit make little sense in this type of model. As equation (9) shows, these bid functions are used only as a prediction of the unobserved losing bids, so determining a measure of fit in that case is impossible. We have provided a pseudo R^2 in table 2 by reporting the correlation between the predicted bid and the actual bid over the uncensored observations. These range from 0.96 to 0.98, suggesting a very good fit for the models. However, the best measure of how well these bids simulate the losing bids comes in the predictive ability of the MNL model, as discussed in the next section.

V. Estimation of the Markdown Model

For the model to estimate bidder markdown, we use some of the same variables as were included in the model of losing bids and augment them with variables specific to the feedlots. Specifically, with reference to equation (7), characteristics, $\mathbf{K}_i^f$, particular to the lot that would contribute to a feedlot's costs and choice of packing plant are identical to those in the bid model (MILES, YIELD, HEAD, PCTPC, PCTYG13). Additionally, the bid variable, W_i^f, in (7) is represented by $\hat{W}_i^f$, a combination of the actual bids and the estimate of the losing bids, as described in equation (9). The MNL model also included additional variables that are related to costs of feedlot production. They include the price of feeder cattle (FEEDER), prices of CORN and HAY, and the current interest rate (INT) for cattle feeding loans (e.g., Jones et al. [1996], Langemeier, Schroeder and Mintert [1992]).[18] The bottom portion of table 1 provides summary information on these additional variables.

In this model, the only variables that are particular to the choice of plant are $\hat{W}_i^f$ and MILES. For MNL models of this type, variables that are equivalent for all choices result in a singularity in the estimation (analogous to the dummy variable trap in linear models). To overcome this problem, we follow the procedure set forth in Greene [2000, p. 859]. The result is three estimates of coefficients for the non-choice specific variables.

One concern was whether the model should be nested to take into account that one firm, Excel, owned two of the four plants. If feedlots looked at both plants as separate buyers, then it is logical to keep the plants separate in the analysis. However, if feedlots considered the two plants to be extensions of a single firm and dealt with either plant in the same way, then perhaps there were only three choices that the feedlots faced, namely, selling to either Excel plant, selling to IBP, or selling to Monfort. To test this question, we estimated two models: one which treated all four plants as separate choices and a nested model that treated the two Excel plants as separate choices on one "branch" of a tree with three branches: sell to Excel, sell to IBP, or sell to Monfort. The results of this nested model were not greatly different from the results of the non-nested model. A test of the nesting structure is whether parameter estimates on what are termed "inclusive values" for the three branches are between zero and one. If they are, then the nested model is appropriate. Estimates equal to zero or one indicate that a non-nested structure is appropriate, while estimates of these parameters less than zero or greater than one are inconclusive. For the nested model, the parameter estimates of the inclusive values for the three

[18] The prices of feeder cattle, corn, and hay came from the Livestock Marketing Association, and the interest rates for cattle feeding loans came from various issues of *The Record Stockman*.

branches were close to one (specifically, the values ranged from 1.08 to 1.12), providing evidence that the nesting structure may be abandoned.[19]

Table 3 provides the statistical properties of the MNL model, along with some commonly used measures of fit, which show that the fit of this model is quite good. McFadden's Likelihood Ratio index is 0.83 and the Veall-Zimmermann adaptation is 0.95.[20] Further, the model correctly predicted the plant that obtained the lot in 88.42% of the observations and predicted the lots that went specifically to plants 1, 2, 3, and 4, respectively, 92.35%, 85.85%, 85.60%, and 85.63% of the time.

Caution must be exercised in interpreting the magnitudes and the signs of the marginal effects in an MNL model because they are not directly tied to the coefficient estimates. Specifically, the marginal effects are equal to $\frac{\partial \rho_i^f}{\partial X_j^f} = \rho_i^f \left[\iota - \rho_j^f \right] \boldsymbol{\beta}$, where $\boldsymbol{\beta}$ is the vector of estimated coefficients, and $\iota = 1$ if i = j and $\iota = 0$, otherwise. The particular marginal effect of interest from the standpoint of evaluating the bidding process is ϖ_i^f, the effect on a feedlot's decision to sell to plant i given plant i's bid. Because of the nonlinearities of discrete choice models, Greene (p. 816) recommends computing the marginal effects at each observation and reporting the sample average of the individual marginal effects. Column 2 in table 4 provides the marginal effects, computed in this manner, for each plant and the average across all plants. On average a one-dollar increase in the bid by a plant results in a 20% increase in the likelihood that the plant will receive the lot. The marginal effects range from 0.133 (plant 1) to 0.262 (plant 2).

[19] Unfortunately, we are unable to report these estimations. A criterion of importance in meeting the nondisclosure requirements for this data set is to not release information summarized from estimations of fewer than four plants.
[20] Both statistics range in the unit interval, with higher values denoting a better fit (Greene [2000]).

We can also estimate the effect of an increase in distance on the probability of selling to a particular plant. These effects were roughly identical for all four plants, showing that an increase in distance between a feedlot and a plant of one mile reduced the probability that a sale would go to that plant by 0.013%. Recall that the sample is restricted to feedlots within a 150-mile radius of the plants, so this value would likely be larger for an analysis of all feedlots included in the data set.

Table 4 also reports the estimates for the Lerner index (equation (8)) and the markdown, ρ_i^f / ϖ_i^f, given in equation (5), using the calculated marginal effects. The Lerner index ranges from 5% to 10%, with an index for all plants of 6.5%. In terms of dollars, the markdown ranges from a low of \$3.40 per cwt to a high of \$6.92 with the average for all plants of \$4.51 per cwt., or an average loss on an average lot transaction of \$10,084.[21]

There is evidence of a spatial pattern to the markdowns, which decline the further a feedlot is from a particular plant. Differentiating the markdown term in equation (5) with respect to MILES (M) gives:

$$\text{(11)} \qquad \partial(\rho_i^f/\varpi_i^f)/\partial M = (\partial\rho_i^f / \partial M)(1-\rho_i^f)^{-2}\beta_W^{-1},$$

where β_W is the coefficient on the $\hat{W}_i^f$ variable in the MNL model. Since the sign of this coefficient is positive and the marginal effect with respect to MILES is negative, it follows that this derivative is negative. The value of this derivative using the above mean values revealed that for every 10-mile increase in distance between a feedlot and a plant, the markdown fell by approximately 2 cents per cwt. This result is consistent with spatial oligopsony wherein a plant faces less competition for cattle from feedlots located in close proximity to the plant.

[21] The average lot in our sample is approximately 2,236 cwt and the average transaction is approximately \$145,000.

VI. Conclusions

This paper has presented an empirical methodology for estimating markups or markdowns from bid data and applied the approach to the controversial U.S. cattle industry, an industry with a complicated auction structure. In general, the markdowns for cattle reported here, in the 5-10% range, are higher than those reported in most of the prior empirical work, e.g., based upon his survey of the literature, Ward [2002] suggested a total distortion (both markup and markdown) in the range of three percent or less. The difference in results may be due to our reliance upon transactions-level data and exploitation of the probabilistic nature of supply inherent in the bidding process for cattle. In contrast, most prior studies have relied upon aggregate time series data and faced the daunting challenge of isolating the impacts on prices of the major exogenous shocks that have buffeted the industry over the past 25-30 years.[22]

Finding markdowns of the aforementioned magnitude should not be especially surprising given the structure of the market (four regional plants, with three firms), and the nature of the bidding process. At a basic level, a first-price auction with affiliated bidders is subject to a winner's curse, and some adjustment of bids relative to ex ante evaluations is required. Probably more importantly, however, are the several features of the bidding environment described here that do not seem consonant with cattle producers' best interest. Nonetheless, policy interpretations based upon these results must be made with circumspection. If plants are operating in the presence of substantial cost economies, as Morrison Paul [2001] has suggested, then some combination of markdown of price to producers or markup of price to

[22] Of course, our results apply only to the Panhandle region of Texas, whereas the results based upon aggregate data apply, in principle, to the entire U.S. It is certainly possible that there are regional differences in markdowns.

wholesalers/retailers is necessary for packers to cover full costs.[23] Also it might be argued that packers are not maximizing profits on a transaction-by-transaction basis as assumed here, and, instead, could be pursuing a more complicated dynamic optimization problem that would cause them to not achieve the transaction-by-transaction markdowns identified in this paper. In this case the results still have value in identifying potential markdowns that could emerge depending upon the market and policy environment.

We believe that this approach represents a useful addition to the toolkit of those who undertake empirical analysis of competition in auction environments. The methodology works well in settings where data are sufficiently rich and abundant to allow a good estimation of each bidder's probability of winning, and is valuable when other approaches are impractical because of the complicated nature of the bidding environment or lack of an identifiable control group of competitive bidders. Many agricultural product markets fit this characterization due to an abundance of transactions and stringent requirements, often imposed by government for record-keeping (for example, see Wilson and Dahl's [2001] analysis of bidding in international wheat contracts). Auctions for commercial real estate (see Quan [1994] for a survey), in market areas where a relatively stable set of bidders participate, may provide a further class of application.

[23] Notably, however, Morrison Paul's dataset for the four-digit manufacturing industry SIC 2011 (meat packing plants) ran from 1958-1991, and her results suggested that cost economies were most important in the early part of her dataset. Arguably, those economies were nearly fully exploited during the 1995-96 time period studied here.

Table 1. Description of Variables.

Variable	Description/Units	Mean (Std. Dev.) for All Plants
Variables used in the Estimation of the Losing Bids		
W	FOB feedlot price for the spot market purchases ($ per cwt)	64.55 (3.78)
BXPR	The boxed beef price reported by the AMS on the day that the lot gets sold. The AMS box beef prices are reported according to whether the beef is "Prime/Choice" or "Select/Other". BXPR is an average of the box beef price from AMS weighted by the percentage of "Prime/Choice" and "Select/Other" in the lot ($/cwt)	99.84 (4.35)
PRFUT	Nearby live cattle futures price, prior day's close ($/cwt)	64.98 (3.77)
YIELD	Lot's total hot weight divided by the total live weight (%)	63.77 (0.94)
HEAD	Number of cattle in the lot.	188.52 (128.21)
PCTYG13	Percentage of lot achieving yield grades 1, 2 or 3 (%)	98.00 (2.69)
PCTPC	Percentage of lot grading prime or choice (%)	53.32 (16.06)
MILES	The distance the cattle were shipped to the plant (miles).	69.57 (82.75)
MILES2	The square of MILES	
AWS	The lot's average carcass weight if the lot consisted of steers, 0 otherwise (lbs.).	1,177.46* (72.27)
AWH	The lot's average carcass weight if the lot consisted of heifers, 0 otherwise (lbs.).	1,073.29* (63.73)
AWM	The lot's average carcass weight if the lot consisted of steers and heifers, 0 otherwise (lbs.).	1127.94* (75.99)
AWS2, AWH2, AWM2	The square of AWS, AWH and AWM, respectively.	
MON-FRI	Daily dummy variables equal to 1 if the transaction occurred on the purchase day indicated, zero otherwise.	Range: low on MON of 0.06 to a high on WED of 0.36.
NRST	Mileage from the selling feedlot to the nearest plant who did NOT procure the lot.	66.49 (88.93)
NRST2	The square of NRST.	
SUP, SUPOTH	The seven-day moving averages of previous purchases per plant and per a plant's rivals, respectively.	3,235 (1,308); 14,381 (2,895)
SUP2, SUPOTH2	The squares of the prior purchase variables.	
WEEK1-WEEK66	Weekly dummy variables equal to 1 if the transaction occurred on the purchase week indicated, zero otherwise.	
Additional Variables used in MNL Model		
BIDS	See equation (9)	63.29 (3.94)
FEEDER	Average weekly price of feeder cattle: average Amarillo and Dodge City prices; all weights ($/cwt)	66.05 (7.09)
CORN	Average weekly price of number 2 corn in the Texas panhandle ($/bu)	3.38 (0.69)
HAY	Average monthly price of alfalfa hay, national average ($/ton)	87.91 (3.26)
INT	Average weekly West Texas interest rate for cattle feeding loans (%)	10.19 (0.28)

*These averages exclude zero-valued observations.

Table 2. Estimation Results for the Losing Bids.

	Plant 1	Plant 2	Plant 3	Plant 4
Constant	D	D	D	D
	(2.1453)	(2.4842)	(2.7254)	(3.4309)
BXPR	0.2950*	0.3073*	0.0460*	0.4132*
	(0.0165)	(0.0175)	(0.0081)	(0.0206)
PRFUT	0.5412*	0.6194*	0.8887*	0.4432*
	(0.0219)	(0.0233)	(0.0164)	(0.0266)
YLD	0.1261*	0.3617*	0.2340*	0.3537*
	(0.0111)	(0.0129)	(0.0151)	(0.0162)
HEAD	-0.0016*	0.0002*	0.0004*	0.0031*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
PCTYG13	-0.0194*	0.0339*	-0.0968*	0.2297*
	(0.0039)	(0.0049)	(0.0053)	(0.0098)
PCTPC	0.0065*	0.0077*	-0.0227*	0.0060*
	(0.0007)	(0.0008)	(0.0009)	(0.0010)
MILES	-0.0012*	0.0037*	-0.0013*	-0.0097*
	(0.0003)	(0.0003)	(0.0003)	(0.0004)
MILES2	-3.73E-05*	-4.50E-06*	2.10E-05*	2.51E-05*
	(1.51E-06)	(1.20E-06)	(1.64E-06)	(1.53E-06)
AWS	0.0591*	0.0662*	0.0455*	0.0952*
	(0.0031)	(0.0036)	(0.0039)	(0.0050)
AWH	0.0661*	0.0744*	0.0530*	0.1056*
	(0.0033)	(0.0039)	(0.0042)	(0.0054)
AWM	6.06E-02*	7.11E-02*	4.81E-02*	9.86E-02*
	(3.31E-03)	(3.77E-03)	(4.11E-03)	(5.23E-03)
AWS2	-2.62E-05*	-2.81E-05*	-1.97E-05*	-4.00E-05*
	(1.32E-06)	(1.51E-06)	(1.65E-06)	(2.10E-06)
AWH2	-3.27E-05*	-3.56E-05*	-2.68E-05*	-4.89E-05*
	(1.53E-06)	(1.76E-06)	(1.92E-06)	(2.47E-06)

(Continued)

Table 2. (Continued)

	Plant 1	Plant 2	Plant 3	Plant 4
AWM2	-2.79E-05*	-3.26E-05*	-2.23E-05*	-4.25E-05*
	(1.55E-06)	(1.72E-06)	(1.86E-06)	(2.33E-06)
MON	0.8454*	2.3685*	-0.4166	0.0753
	(0.2785)	(0.4536)	(0.2171)	(0.3255)
TUE	0.6701*	2.1733*	-0.8000*	0.4025
	(0.2775)	(0.4523)	(0.2148)	(0.3214)
WED	1.1932*	2.7195*	-0.4246	0.6376
	(0.2766)	(0.4520)	(0.2129)	(0.3204)
THU	1.2041*	2.5042*	-0.5152*	0.4983
	(0.2754)	(0.4514)	(0.2121)	(0.3185)
FRI	0.9844*	2.4783*	-0.7121*	0.4801
	(0.2766)	(0.4524)	(0.2152)	(0.3205)
NRST	-5.39E-03*	-9.93E-04*	3.78E-03*	5.91E-03*
	(3.12E-04)	(3.88E-04)	(4.15E-04)	(4.55E-04)
NRST2	4.14E-05*	-8.33E-06*	-4.16E-05*	-3.31E-05*
	(1.37E-06)	(1.34E-06)	(1.92E-06)	(1.96E-06)
SUP	-7.45E-04*	6.81E-04*	8.25E-04*	9.12E-04*
	(6.09E-05)	(5.76E-05)	(6.56E-05)	(7.25E-05)
SUP2	1.35E-08*	-5.94E-08*	-5.37E-08*	-7.13E-08*
	(6.65E-09)	(5.66E-09)	(6.03E-09)	(6.85E-09)
SUPOTH	4.96E-04*	1.08E-04*	-1.03E-04*	-4.36E-06
	(3.99E-05)	(4.14E-05)	(4.96E-05)	(4.90E-05)
SUPOTH2	-1.14E-08*	-4.82E-09*	-5.51E-10	-9.61E-10
	(1.27E-09)	(1.36E-09)	(1.67E-09)	(1.65E-09)
Log-likelihood	-15,215.55	-15,021.86	-10,007.91	-9,480.88
Pseudo-R^2	0.9713	0.9800	0.9568	0.9623

Notes: * indicates significance at the 5% hypothesis-test level.
D denotes a coefficient that is not reported to preserve confidentiality of firm-level data.

Table 3. Coefficient Estimates from the MNL Model.

Variable	*Estimate*	*Std. Error*	*t Value*
$\hat{W}_i^f$	3.38600	0.04570	74.17
MILES	-0.00231	0.00070	-3.31
FEEDER(1)	-0.03820	0.02770	-1.38
FEEDER(2)	-0.06460	0.02430	-2.66
FEEDER(3)	0.01800	0.02580	0.70
CORN(1)	-0.31970	0.27190	-1.18
CORN(2)	-0.81610	0.23830	-3.42
CORN(3)	0.20660	0.24810	0.83
HAY(1)	0.03110	0.02290	1.36
HAY(2)	-0.02690	0.01830	-1.47
HAY(3)	-0.09090	0.01850	-4.91
INT(1)	0.00019	0.00005	3.55
INT(2)	0.00005	0.00004	1.22
INT(3)	-0.00008	0.00005	-1.75
YLD(1)	-0.04000	0.04960	-0.81
YLD(2)	0.03000	0.04520	0.66
YLD(3)	-0.08740	0.04570	-1.91
HEAD(1)	-0.00109	0.00051	-2.15
HEAD(2)	0.00050	0.00040	1.25
HEAD(3)	-0.00004	0.00037	-0.11
PCTPC(1)	0.01810	0.00414	4.38
PCTPC(2)	0.01020	0.00373	2.73
PCTPC(3)	0.02120	0.00408	5.20
PCTYG13(1)	0.01280	0.02950	0.43
PCTYG13(2)	0.06310	0.02880	2.19
PCTYG13(3)	0.11650	0.02930	3.98
Log Likelihood	-3,950		
McFadden's LRI	0.8279		
Veall-Zimmermann	0.9478		
Percent Correct Predictions	88.42		

Table 4. Marginal Effect of a Bid on the Choice of Plant, Lerner Index, and Markdown.

	Mean Effect of Bid On Choice of Plant	Lerner Index (%)	Markdown/cwt ($)
Plant 1	0.133	9.64%	$6.92
Plant 2	0.253	4.99	3.40
Plant 3	0.213	5.91	4.03
Plant 4	0.249	5.09	3.45
All Plants	0.196	6.51	4.52

References.

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

Azzam, A. and D. Anderson, 1996, “Assessing Competition in Meatpacking: Economic History, Theory and Evidence”, U.S. Department of Agriculture, GIPSA-RR 96-6 (May).

Bajari, P. and L. Ye, 2003, “Deciding Between Competition and Collusion”, *Review of Economics and Statistics*, in press.

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

Blair, R.D. and J.L. Harrison, 1993, *Monopsony: Antitrust Law and Economics*, Princeton, NJ: Princeton University Press.

Campo, S., I. Perrigne, and Q. Vuong, 2003, “Asymmetry in First-Price Auctions with Affiliated Private Values”, *Journal of Applied Econometrics*, in press.

Campo, S., I. Perrigne, and Q. Vuong, 2002, “Semiparametric Estimation of First-Price Auctions with Risk Averse Bidders”, Working Paper, University of Southern California.

Christie, W. G. and P. H. Schultz (1994). “Why Do NASDAQ Market Makers Avoid Odd-Eighth Quotes?” *Journal of Finance* 49: 1813-40.

Crespi, J.M. and R.J. Sexton, 2002, “Bidding for Cattle in the Texas Panhandle”, Selected paper presented at the annual meetings of the American Agricultural Economics Association, (July 29) Long Beach, California.

Economist, The, “Learning to Play the Game”, May 17, 1997**:** 86.

Garcia-Diaz, A. and P.L. Marin, 2003, “Strategic Bidding Behavior with Short-Lived Bids: An Application to the Spanish Market”, *International Journal of Industrial Organization*, 21: 201-222.

Goeree, J., C. Holt, and T. Palfrey, 2002, “Quantal Response Equilibrium and Overbidding in Private-Value Auctions”, *Journal of Economic Theory*, 104: 247-272.

Graham, D. and R. Marshall, 1987, “Collusive Bidder Behavior at Single-Object Second-Price and English Auctions”, *Journal of Political Economy*, 95: 975-994.

Greene, W.H., 2000, *Econometric Analysis*, Fourth Ed. Prentice Hall, Upper Saddle River, New Jersey.

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

Hunnicutt, L., D. Bailey, and M. Crook, 2002, "Measuring Market Power with Variables Other Than Price", Selected paper presented at the annual meetings of the American Agricultural Economics Association (July 29), Long Beach, California.

Jones, R., J. Mintert, M. Langemeier, T. Schroeder, and M. Albright, 1996, *Sources of Economic Variability in Cattle Feeding*. NCR-134 Conference: Applied Commodity Price Analysis, Forecasting, and Market Risk Management, Chicago, Illinois.

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

Laffont, J.-J., H. Ossard, and Q. Vuong, 1995, "Econometrics of First-Price Auctions", *Econometrica*, 63: 953-980.

Langemeier, M., T. Schroeder and J. Mintert, 1992, "Determinants of Cattle Finishing Profitability", *Southern Journal of Agricultural Economics*, 24: 41-47.

McEowen, R. A., P. C. Carstensen and N.E. Harl, 2002, "The 2002 Senate Farm Bill: The Ban on Packer Ownership of Livestock", *Drake Journal of Agricultural Law*, **7**: 267-304.

McFadden, D., 1973, "Conditional Logit Analysis of Qualitative Choice Behavior", in P. Zarembka, ed., *Frontiers in Econometrics*. Academic Press, New York.

Monier-Dilhan, S. and H. Ossard, 1998, "Producers' Loss Due to Asymmetric Information: An Application to a Specific Case", *European Review of Agricultural Economics*, 25: 155-169.

Morrison Paul, C.J., 2001, "Cost Economies and Market Power: The Case of the U.S. Meat Packing Industry", *Review of Economics and Statistics*, 83: 531-540.

Paarsch, H.J., 1992, "Deciding Between the Common and Private Value Paradigms in Empirical Models of Auctions", *Journal of Econometrics*, 51: 192-215.

Pesendorfer, M, 2000, "A Study of Collusion in First-Price Auctions", *Review of Economic Studies*, 67: 381-411.

Pore, R., "Daschle: Tighter anti-trust enforcement needed", *Huron (S.D.) Plainsman*, June 3, 2002.

Porter, R.H., 1995, "The role of Information in U.S. Offshore Oil and Gas Lease Auctions", *Econometrica*, 63: 1-27.

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: 263-88.

Purcell, W.D., 2000, “Measures of Changes in Demand for Beef, Pork, and Chicken, 1975-2000.” Research Bulletin 4-2000 (December), Research Institute on Livestock Pricing, Virginia Tech University.

Quan, D.C., 1994, “Real Estate Auctions: A Survey of Theory and Practice”, *Journal of Real Estate Finance and Economics* 9: 23-49.

Riley, J.G. and W.F. Samuelson, 1981, “Optimal Auctions”, *American Economic Review*, 71: 381-392.

Rogers, D. “Ranchers Again See Need to Fight MeatPackers' Grip on Livestock”, *The Wall Street Journal*, March 13, 2002.

Rosen, S., K.M. Murphy, and J.A. Scheinkman, 1994, “Cattle Cycles”, *Journal of Political Economy,* 102: 468-92.

Schroeder, T.C., R. Jones, J. Mintert, and A.P. Barkley, 1993, “The Impact of Forward Contracting on Fed Cattle Prices”, *Review of Agricultural Economics*, 15: 325-337.

Schroeter, J.R. and A. Azzam. “Econometric Analysis of Fed Cattle Procurement in the Texas Panhandle.” Report submitted in fulfillment of Cooperative Agreement No. 98-PPD-01, U.S. Department of Agriculture, Grain Inspection, Packers and Stockyards Administration, November 1999.

Schroeter, J.R. and A. Azzam, 2002a, “Captive Supplies and the Spot Market Price of Fed Cattle: The Plant-level Relationship”, Working paper, April.

Schroeter, J.R. and A. Azzam, 2002b, “Captive Supplies and Cash Market Prices for Fed Cattle: Do Delivery Timing Incentives Explain the Short-run Relationship?” Working Paper.

Sexton, R.J., 2000, “Industrialization and Consolidation in the U.S. Food Sector: Implications for Competition and Welfare”, *American Journal of Agricultural Economics*, 82: 1087-1104.

U.S. Department of Agriculture, 2000, *Packers and Stockyards Statistical Report: 1998 Reporting Year*, Grain Inspection, Packers and Stockyards Administration, SR-00-1 (July).

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

Ward, C.E., 1982, “Relationships Between Fed Cattle Market Shares and Prices Paid by BeefPackers in Localized Markets”, *Western Journal of Agricultural Economics*, 7: 79-86.

Ward, C.E., 1981, “Short-Period Pricing Models for Fed Cattle and Impacts of Wholesale Carcass Beef and Live Cattle Futures Market Prices”, *Southern Journal of Agricultural Economics*, 13: 125-132.

Ward, C.E. and T. Schroeder, 2000, “Structural Changes in Cattle Feeding and Meat Packing”, Oklahoma Cooperative Extension Service, Extension Facts WF-553.

Wilson, W.W. and B.L. Dahl, 2001, “Import Tenders and Bidding Strategies in Wheat”, *Review of Agricultural Economics* 23: 441-457.

Appendix.

We can rewrite equation (5) in terms of the feedlot's supply response to packer i's bid. Let $P^f - c_i = P$ for simplicity, and delete the superscripts and subscripts. Equation (5) is then given by (A1):

(A1) $$P = \rho / \varpi + W \text{, or}$$

$$P = \rho / [\partial\rho / \partial W] + W .$$

Multiply the first term of the above equation by W/W and by Q/Q and rewrite:

(A2) $$P = W\left[1 + \frac{\rho}{W}\frac{1}{\partial\rho/\partial W}\frac{Q}{Q}\right] = W\left[1 + \frac{\rho Q}{W}\frac{1}{\partial\rho/\partial W}\frac{1}{Q}\right].$$

Recall that the expected supply in equation (2) is ES = $\mathbf{D}$Q, so $(\partial\rho / \partial W)Q = \partial ES / \partial W$. Using this result, we can rewrite equation (A2) as:

$$P = W\left[1 + \frac{ES}{W}\frac{\partial W}{\partial ES}\right] = W\left[1 + \frac{1}{\varepsilon}\right] \text{, or}$$

(A3) $$(P - W)/W = 1/\varepsilon ,$$

where $\varepsilon = (\partial ES / \partial W)(W / ES)$ is the probabilistic, bid-response elasticity for a feedlot selling to packer i.

First consider the case where the N packers are symmetric in their bidding, cost structures, plant sizes, desire for quality characteristics, etc., such that there is an equal likelihood for any packer to get a lot of cattle and $\mathbf{D}$=1/N. In this case, $\varepsilon = (\partial ES / \partial W)(W / Q)N$. As N increases, the feedlot's bid response elasticity also increases, and the markdown approaches the competitive one. Second, consider the simple monopsony case where $\mathbf{D}$=1 and ES=Q. In this case $\varepsilon = (\partial Q / \partial W)(W / Q)$, the typical non-stochastic supply response from a feedlot to the monopsony's bid.