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Competitive Bidding on Import Tenders: The Case of Minor Oilseeds

William W. Wilson and Matthew A. Diersen

A common and noteworthy application of auctions and bidding is that of tendering for imports, used for both price determination and the allocation of purchases among sellers. In this study we develop a model to evaluate bidding strategies and competition and apply it to Egyptian oilseeds imports. Generally, bids could be explained with a relatively high degree of confidence using accessible data. In addition, there appear to be groups of bidders characterized by differences in their bid functions. These statistical results were used to determine optimal bids and evaluate the effects of several critical variables. The results are particularly interesting for understanding sellers' bidding strategies and competition among rivals, as well as impacts of specific variables on optimal bids and payoffs to sellers.

Key words: auction, bidding, grains, importing, international grain competition, oilseeds

Introduction

Bidding competition plays an important role in many aspects of agricultural marketing. Transaction prices are discovered through bidding, and purchases are allocated among rivals. Alternatives to bidding are other forms of pricing, including negotiation and posted prices. Because of the efficiency of bidding competition in fulfilling the roles of price discovery and allocation, bidding is used in numerous commodities, products and services in commerce, and agricultural marketing. Recent examples range from bidding on spectrum rights to airwave auctions, and numerous forms of internet-based auctions. Examples in grain marketing include bidding for forward cash contracts, import tenders and Export Enhancement Program (EEP) subsidies, the allocation of Commodity Credit Corporation (CCC) stocks, recent adoption in rail service (Wilson, Priewe, and Dahl), and tendering in international wheat competition (Wilson and Dahl 2001). Bidding has also been adopted recently for Japanese import tenders for barley (Rampton) and was proposed as a mechanism for port-buying in marketing Canadian wheat.

There are several questions about bidding of particular importance and interest to importers and exporters in the international grain and oils trade. These questions relate to: (*a*) identification of competitor bidding strategies, (*b*) determination of optimal bids,

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(*c*) the effect of the number of bidders on bidding competition, and (*d*) how information affects bidding competition among participants. These concerns are frequently raised by participants, and have not been addressed in the agricultural economics literature.

The primary objective of this study is to analyze strategies of competitors and effects of critical variables on auctions, building upon recent advances in auction theory and bidding. A model of bidding competition is applied using actual data from Egyptian import tenders for sun oil bought internationally. In the following section, we review previous studies and develop a theoretical model of bidding. Next, a statistical analysis of the tender results is provided, followed by a discussion of the bidding model and factors affecting optimal bids. Of particular interest is the effect of the number of bidders and information on bidding strategies. The article concludes with a summary of implications for buyers and sellers in the industry.

Analytical Models of Bidding Competition

Both Cassady and Brown provide historical overviews of auction strategies and mechanisms. Several bibliographies (McAffee and McMillan 1987, 1996b; Engelbrecht-Wiggans; Milgrom 1985, 1987, 1989; Rothkopf and Harstad; Wilson 1992) review the literature on auctions and bidding strategies. Recent texts detail some practical motivations for auctions and analytical approaches to bidding strategies (Monroe; Nagle and Holden; Lilien and Kotler; Rasmusen; Kottas and Khumawata; Sewall).

Auction mechanisms have come into vogue in recent years as procedures for allocating assets in certain industries following deregulation (Shebl; Kuttner; McMillan 1994; McAfee and McMillan 1986), and have been revered in popular magazines (Norton; *The Economist* staff). Indeed, numerous recent studies have applied these techniques (Crampton 1995; Hendricks and Porter; Hendricks, Porter, and Wilson; McAfee and McMillan 1996a, b; Porter and Zona). Recent examples in agriculture are summarized in Sexton (pp. 189–95), with subsequent applications to import tendering for wheat (Wilson and Dahl 2001), European Union (EU) export tenders (Bourgeon and LeRoux 1996a, b), price transparency (Wilson, Dahl, and Johnson), and the Conservation Reserve Program (Latacz-Lohmann and Van der Hamsvoort).

A strain of the literature (e.g., Lilien and Kotler; Engelbrecht-Wiggans; Rothkopf and Harstad) uses decision models based on the individual decision maker's strategy, taking competitors' strategies as given. We develop this approach here, consistent with other research analyzing strategies of individual players (e.g., Crampton 1995, 1997).

Theoretical Model

The model is of a single player bidding against an uncertain number of opponents. The bidder determines a profit-maximizing bid considering the likelihood of underbidding opponents. An important feature of the analysis involves determining opponents' bid distributions. Bayesian posterior distributions are used to solve this problem and allow the bidder to account for differences across opponents.

Conventional Approaches

Monroe; Lilian and Kotler; and Nagle and Holden demonstrate various approaches to deriving opponents' bid distributions, which ultimately are used to derive optimal bids. The approach closest to that used in this study is the *specific-opponent approach* (Monroe; Nagle and Holden, pp. 203–04) where information exists on past bidding behavior of individual opponents. Factors affecting bidding competition are the number of competitors, their distributions of bids, and whether they consistently bid in different auctions. However, implementation requires derivation of the opponents' bid distribution. Lilian and Kotler suggest computing the historic distribution of the ratio of an opponent's bids to the bidder's cost. While this method provides a probability distribution, it is a marginal distribution of a modified variable (the ratio of bids to costs), and thus has limited usefulness.

Bidder Objective Function

The bidder's objective is to maximize expected profit, the difference between the bid and cost weighted by the likelihood of winning. The optimal bid is influenced by the probability of underbidding all opponents, which is a function of the bid. The bidder seeks to maximize:

$$E(\pi) = (B - C)W(B), \tag{1}$$

where $E(\pi)$ is the expected profit, B is the bid, C is the bidder's cost, and $W(B)$ is the probability of underbidding all opponents.

The crucial unknown factor from the bidder's perspective is $W(B)$, and its estimation is necessary to derive an optimal bid. Each opponent has a bid, V_j, with a density, $f_j(V_j)$. With a known density, the probability that an opponent's bid is less than B can be derived as:

$$F_j(B) = \Pr(V_j \leq B). \tag{2}$$

Because the lowest bid is the winning bid, the probability of winning, or underbidding the opponent with a bid of B, is $1 - F_j(B)$. Thus, with a single opponent:

$$W(B) = 1 - F_j(B), \tag{3}$$

and with multiple independent opponents:

$$W(B) = \prod_{j=1}^{j} \left[1 - F_j(B)\right]. \tag{4}$$

In the special case where an opponent does not bid in every auction, the probability in (2) can be transformed to:

$$\tilde{F}_j(B) = p_j F_j(B) + (1 - p_j), \tag{5}$$

where p_j is the probability that the opponent bids. The transformed probability in (5) is weighted by the likelihood of the opponent bidding, and can then be used in (3) and (4) if appropriate.

Bid Functions and Bidding Behavior

The auction results are released ex post, which allows opponents' bids to be analyzed relative to proxies of expected costs. Relating an opponent's bids to values of a readily observable cost indicator facilitates forecasting expected bids and their distributions. A cost indicator C_{jt}, and past bids V_{jt}, for each opponent j were used to estimate a bid function. A linear bid function for each opponent j was specified as:

$$V_{jt} = \alpha_j + \beta_j C_{jt} + \varepsilon_{jt}, \qquad j = 1, \ldots, J;\ t = 1, \ldots, T, \tag{6}$$

where ε_{jt} is $\sim N(0, \sigma_j^2)$. Although subscripted for time, (6) is pooled over n_j bids and is not necessarily a continuous time series. Because the parameters α_j and β_j, and the error term ε_{jt}, are opponent-specific, forecasts and distributions were derived for each individual bidder.

Bayesian Predictive Distribution

A full characterization of the opponent's bid distribution is necessary to obtain the desired probability distribution in (2). A Bayesian setting is a method to obtain the predictive density of an opponent's future bid, $f(V_{T+1})$. The subscript j is suppressed here to simplify the notation, but a distinct bid distribution is necessary for each opponent, and $T + 1$ reflects out-of-sample derivations. Press shows that with a vague prior density on α and β in (6), and conditioning them on the sample, both will have t-posterior distributions. With posterior distributions for α and β, and a new value of the cost indicator, C_{T+1}, a characterization of the predictive density of V_{T+1} is possible. The density, $f(V_{T+1}|D_{T+1})$, is conditioned on D_{T+1}, the opponent's specific sample information at the time the bid function is calculated.

Using ordinary least squares (OLS) parameter estimates from (6) for each opponent, the expected bid is $\hat{V}_{T+1} = \hat{\alpha} + \hat{\beta}C_{T+1}$. The predictive distribution is thus centered around the expected bid. Because the posterior distributions for α and β follow t-distributions, $f(V_{T+1}|D_{T+1})$ also follows a t-distribution. Any potential bid, V_{T+1}, can be associated with a probability because:

$$\frac{V_{T+1} - \hat{\alpha} - \hat{\beta}C_{T+1}}{\hat{\sigma}\sqrt{1 + \frac{1}{n} + \frac{(C_{T+1} - \bar{C})^2}{\sum_{t=1}^{n}(C_t - \bar{C})^2}}} \Big| \sim sample\ t_{n-2}, \tag{7}$$

where $\hat{\sigma}$ is the standard error of the regression (SER), and n is the number of observations, both opponent-specific. A proof and expansion of the relation in (7) are found in Zellner, and in Press. The location and shape of the predictive density depend on opponent-specific parameters including the parameter estimates and standard error from (6), the number of past observations, and the deviation of the current cost indicator from the mean cost. This follows because the variance of the predictive distribution enters the denominator in (7) (Zellner, p. 74). Thus, as more bids are observed for an opponent, the parameter estimates from its bid function may not change, but the uncertainty of its bid distribution is reduced.

Obtaining probabilities using (7) is straightforward, and (7) can be used to derive probabilities for any potential bid. For example, the probability associated with the mean of the opponent's posterior distribution, V_{T+1}, can be derived. Substituting $\hat{V}_{T+1}$ into the left-hand side of (7) for V_{T+1} results in a zero in the numerator. The probability from the t-distribution with $n - 2$ degrees of freedom for the value zero is 0.5. The probability associated with any other potential bid relative to the specific opponent's predictive bid distribution is found similarly. For a comparable application of this technique, see Zellner, Hong, and Min. The probability of interest is the necessary probability shown in (2)—i.e., that the opponent's bid will be less than the bidder's bid, B_{t+1}. This probability is found by substituting B_{T+1} for V_{T+1} in (7) and finding the associated probability from a t-table. Given bid functions and predictive distributions for each opponent, the probability of underbidding all opponents in (4) for any given future bid can be derived.[1]

Impacts of Information on Bidding Strategy

Changes in the knowledge of an opponent's bid distribution influence both the behavior of other bidders and tender outcomes. Following Rothkopf, an opponent with a uniform bid distribution is modeled.[2] This assumption yields comparative marginal analysis results with closed forms. Consider a bidder having only one rival, with a uniform bid distribution with min $= X$ and max $= Y$. Given X, Y, and C, the bidder chooses a bid, b_1, to maximize expected payoff.[3] The payoff associated with b_1 and the probability of underbidding the opponent determine the expected payoff as:

$$E(\pi) = (b_1 - C)\frac{(Y - b_1)}{(Y - X)}. \tag{8}$$

The bid that maximizes expected payoff satisfies the first-order condition:

$$\frac{dE(\pi)}{db_1} = \frac{(Y - 2b_1 + C)}{(Y - X)} = 0.$$

For this to hold, the numerator in the first-order condition must equal zero. Solving for b_1^* gives:

$$b_1^* = \frac{(Y + C)}{2}, \tag{9}$$

which is the midpoint of the sum of the bidder's own cost and the opponent's highest potential bid. Substituting (9) into (8) yields the maximum expected payoff, which can be stated as:

$$E(\pi^*) = \frac{(Y - C)^2}{4(Y - X)}. \tag{10}$$

[1] This method for determining the optimal bid does not require a closed form for the distributions. Numerical search procedures were used to obtain the optimal bid.

[2] Rothkopf shows the profit-maximizing bid for a bidder in an auction to buy a good against an opponent with a uniform bid distribution. The bidding situation is reversed to demonstrate the selling auction in this study.

[3] We use b_1 in this representation since it refers to results derived from a uniform distribution. This is distinguished from B in the previous section where a t-distribution was used.

Imperfect information introduces greater uncertainty about the rival's bids. An increase in the variance of bids can be represented by adding δ to the tails of the distribution (i.e., $Y+\delta, X-\delta$). The payoff is unchanged at $b_1 - C$, but the probability of winning changes the expected payoff to:

$$E(\tilde{\pi}) = (b_1 - C)\frac{(Y + \delta - b_1)}{(Y + 2\delta - X)}. \tag{11}$$

The payoff-maximizing bid is derived by solving the first-order condition:

$$\frac{(Y + \delta - 2b_1 + C)}{(Y + 2\delta - X)} = 0.$$

Solving for b_1^* gives:

$$b_1^* = \frac{(C + Y + \delta)}{2}. \tag{12}$$

This result indicates that if the variance of the opponent's bids increases by δ, the optimal response is to increase the bid. A smaller variance encourages lower bids. Substituting (12) into (11) reduces to:

$$E(\tilde{\pi}^*) = \frac{(Y + \delta - C)^2}{4(Y + 2\delta - X)}. \tag{13}$$

The extent to which bidder 1's expected payoff changes due to a change in the variance can be evaluated. First, the effect of a change in δ on $E(\tilde{\pi}^*)$ is:

$$\frac{\partial E(\tilde{\pi}^*)}{\partial \delta} = \frac{(Y + 2\delta - X)(Y + \delta - C) - (Y + \delta - C)^2}{2(Y + 2\delta - X)^2}. \tag{14}$$

The sign of (14) depends on the sign of $(Y+2\delta-X)$ relative to $(Y+\delta-C)$. If $Y+2\delta-X>(\leq)$ $Y+\delta-C$, then

$$\frac{\partial E(\tilde{\pi}^*)}{\partial \delta} >(\leq)\ 0.$$

This expression simplifies to:

$$\frac{\partial E(\tilde{\pi}^*)}{\partial \delta} \begin{cases} = 0 & \text{if } C = X - \delta, \\ > 0 & \text{if } C > X - \delta, \\ < 0 & \text{if } C < X - \delta. \end{cases} \tag{15}$$

If bidder 1's cost is above (below) the opponent's new minimum expected bid, the result indicates that increasing the variance raises (lowers) the expected payoff from the optimal bid. In general, if bidders submit profit-maximizing bids, the expected profit increases if their cost is above the opponent's lowest bid submitted. For bidders with cost above the lowest bid submitted, they would see a decrease in expected payoff from an increased variance of opponents' bid distributions.

Similarly, the partial derivative of the payoff equation in (11) with respect to δ is:

$$\frac{\partial E(\tilde{\pi})}{\partial \delta} = \frac{\partial}{\partial \delta}\frac{(b_1 - C)(Y + \delta - b_1)}{(Y + 2\delta - X)}, \tag{16}$$

which reduces to

$$\frac{(b_1 - C)(2b_1 - X - Y)}{(Y + 2\delta - X)^2}.$$

Note that $b_1 - C > 0$ for all bids above cost and $(Y+2\delta - X)^2$ is always > 0. Thus, the sign of $\partial E(\tilde{\pi})/\partial\delta$ depends on bidder 1's bid relative to the opponent's bid,

$$\text{(17)} \qquad \frac{\partial E(\tilde{\pi})}{\partial\delta} \begin{cases} = 0 & \text{if } b_1 = \dfrac{(X+Y)}{2}, \\ > 0 & \text{if } b_1 > \dfrac{(X+Y)}{2}, \\ < 0 & \text{if } b_1 < \dfrac{(X+Y)}{2}. \end{cases}$$

From these results, increasing the variance raises (lowers) the profit from bidder 1's bids that are above (below) the mean of the opponent's bid distribution. Hence, if the bidder submits relatively high bids—bids above the opponent's mean—then expected payoff from those bids would increase. The results in (17) give insight into how an opponent affects expected payoff. When the bid, b_1, equals the mean of the opponent's bid, any change in variance only changes the tails of the distribution and does not affect the probability of underbidding.

Statistical Analysis of Competitor Bidding in Minor Oilseeds

Data Sources

A data set was developed from sun oil tenders received by the Egyptian procurement agency responsible for importing vegetable oils. Primary data were received from the Egyptian procurement agency and used to develop the data for this study.[4] The time period covers all tenders from January 1990 through August 1993. Suppliers are exporting firms, some being both the processor and exporter, others being processors' agents.

There were 26 tenders for sun oil and a total of 397 bids. Over the three-year period, 20 different firms submitted bids in sun oil tenders. The number of firms submitting bids varied over time as did the number of bids each submitted. The average number of firms per tender was eight. The maximum number of separate bidders in a single tender was 11. Sometimes suppliers made multiple offers at different bids (i.e., scaled bids), a common practice in international tendering. For this analysis these were each treated as separate offers by that particular supplier.

Bid Functions

Bid functions were estimated using OLS for each type of oil for each firm as: $V_{jt} = \alpha_j + \beta_j C_{jt} + \varepsilon_{jt}$. The following cost indicators were evaluated to determine which best characterized bidding behavior: Rotterdam and New Orleans prices for sun oil, Chicago Board

[4] This paper summarizes results presented in Wilson and Diersen, who report similar results for cottonseed and palm oil.

Table 1. Bid Functions by Firm in Sun Oil Tenders

Firms Tendering Bids	No. of Bids	Bid Function		SER	R^2	Prob. of Bidding
		Intercept	Slope			
A_s	17	91.08	1.21*	10.08	0.90	0.31
B_s	25	53.50	0.89*	8.87	0.81	0.46
D_s	37	12.90	0.97*	9.97	0.88	0.69
E_s	23	45.36	1.10*	10.61	0.87	0.73
F_s	51	45.21	0.92*	8.37	0.86	0.96
G_s	72	5.95	0.99*	8.47	0.93	0.92
J_s	28	60.38*	1.12*	7.35	0.96	0.46
N_s	24	-3.55	1.01*	8.20	0.86	0.26
O_s	38	20.49	1.04*	7.50	0.96	0.65
P_s	34	83.64	0.83*	12.82	0.62	0.65
Pooled:	349	6.57	0.99*	9.53	0.89	

Note: An asterisk (*) denotes significance at the 10% level.

of Trade (CBOT) soybean oil, and the equivalent of a proposed oilseed price index.[5] These are taken to selectively represent the time series variability in costs of rivals. All alternatives were rejected in favor of Rotterdam sun oil. Results of these and other tests are reported in Wilson and Diersen.

Results for the bid functions are shown in table 1.[6] Bid functions of the pooled sample and major suppliers are shown for comparison purposes. The R^2s are relatively high. The standard error of the regression (SER) gives the average deviation of bids from the regression line and provides a measure of predictive accuracy. The coefficients indicate that supplier firms J_s and O_s are relatively predictable competitors, while supplier firms P_s and E_s are less predictable. Also shown is the probability of bidding, the fraction of tenders for which the firm submitted offers, which ranges from 0.26 to 0.96 across sun oil competitors. Specifically, N_s, A_s, J_s, and B_s submitted offers in less than 50% of the tenders. The effect of sporadic or random bidders is an important component in determining optimum bids.

There appear to be distinct groups of firms participating in these tenders, characterized by the coefficients of their bid functions. Firms A_s, J_s, E_s, and O_s have a high intercept, and a relatively large slope. In comparison, N_s, G_s, and D_s have small intercepts and slopes. Firms in the third group have very large intercepts, and slopes substantially less than one. This latter group is also characterized by relatively poor fitting bid functions, suggesting more erratic bidding behavior. Tests were conducted among rivals with more than 30 bids to determine if the bid functions were statistically different. The null hypothesis was rejected in 6 of the 10 pairings.[7] This finding confirms most bidders

[5] These data are from the Chicago Board of Trade (CBOT) International Edible Oils Index futures contract which traded briefly during the mid-1990s.

[6] Only 10 bidders had sufficient observations for individual estimation in the case of sun oil.

[7] To test equivalence of the bid function across firms, the sum of squared errors (ESS) of the restricted and unrestricted models are compared. The F-statistic is given by

$$\frac{(ESS_R - ESS_{UR})/2}{ESS_{UR}/(n1 + n2 - 4)},$$

where the restricted model is from a pooled sample of two bidders and the unrestricted is the sum of individual bidders' ESS.

Table 2. Bids Needed to Underbid Individual Opponents with Specified Probabilities

Firms Tendering	Probability of Winning		
	0.25	0.50	0.75
	--- Highest Bid Potential vs. Specified Opponents --- ($/mt)		
D_s	504	497	490
F_s	510	503	498
G_s	505	499	493
O_s	504	499	493
P_s	508	499	490

are characterized by different bid functions. Strategically, bidding strategies of firms are clearly different, likely reflecting differences in their fixed and marginal costs.

Bidding Strategies

To illustrate the bidding model, optimal bids were derived for a prototypical bidder denoted as bidder k. An optimal bid and expected payoff were derived for bidder k competing against all rivals. Sensitivity analysis was used to demonstrate effects of critical variables on optimal bids and expected payoffs.

Competitors' Bid Distributions

Estimated bid functions for competitors were used to obtain probability distributions (specifically, t-values derived from bid function relationships) and to formulate bidding strategies. For illustration, assume $C_k = C = \$500$/mt for deriving bids for bidder k (i.e., k's cost is \$500 and equal to the cost indicator). For different values of bidder k's bids, values and probabilities were derived, i.e., the probability of individual opponents bidding at or below bidder k's offer. To demonstrate changes in the optimal bid, a subset of rivals (those with at least 30 bids) was chosen.

Optimal bids to win against individual rivals are reported in table 2. The values shown are bids needed to underbid opponents with different probability levels. For example, \$510/mt is the bid needed to underbid F_s, with a probability of winning of 0.25 if F_s were the only competitor. From this table, F_s is likely to bid highest, and P_s has the most uncertainty. The expected payoff functions for bidder k against specific bidders are illustrated in figure 1.

Given the probability of winning for different bids, the optimal bid against the different opponents could be derived. The expected payoff peaks at \$510/mt against opponents F_s and P_s, making that the optimal bid. The expected payoff associated with the optimal bid is highest when bidding only against F_s, who tends to bid high. Bidding is profitable over a wide range of bids against P_s, who has the highest range of bids and the highest standard error in the bid function.

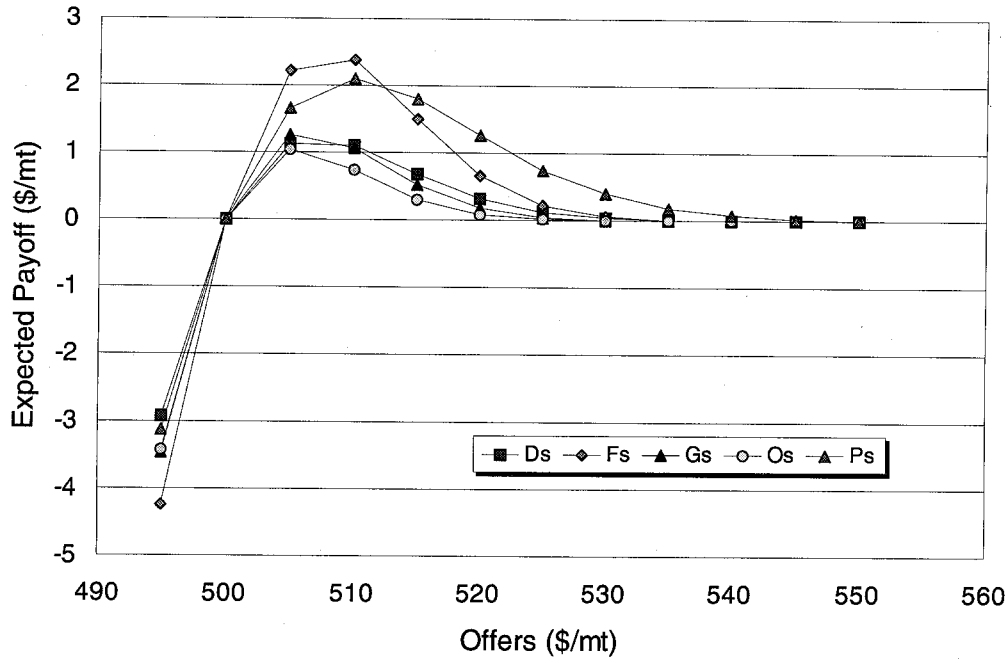

Figure 1. Sun oil tenders: Expected payoff of different bids by major bidders

Factors Affecting the Optimal Bid

The optimal bid for bidder k was derived from the above distributions. Several critical factors affect the optimal bids which were analyzed using simulations and are described below.

Number of Bidders

From a bidder strategy perspective, higher bids result in a greater payoff, but also a lower probability of winning. The product of these two functions yields the expected payoff, $E(\pi)$. The probability of underbidding more than one opponent is the joint probability of underbidding each opponent separately, as shown in equation (4). Thus, additional rivals reduce the probability of winning. A reduction in the number of bidders increases $W(B)$, and as a result the optimal bid increases, as does $E(\pi)$. An important parameter affecting bidding competition is the number of bidders, the effect of which is addressed below.

To demonstrate these effects, bidders were added in order of likelihood of submitting a bid, and the joint probability of winning was computed for each set of bidders. The optimal bid and $E(\pi)$ are shown in table 3. Increasing the number of bidders from one to five (the average was eight for sun oil) shifts the joint bid distribution and reduces the optimal bid and expected payoffs. With only F_s bidding, the optimal bid is $508/mt. Adding G_s as a rival lowers the optimal bid to $505/mt, and the expected payoff from the optimal bid also declines from $2.74/mt to $0.73/mt. Even the addition of a fifth bidder lowers the expected payoff by a noticeable amount.

Table 3. Sun Oil Tenders: Effects of Number of Bidders

No. of Bidders	Firms Included	Optimal Bid ($/mt)	Expected Payoff ($/mt)
1	F_s	508	2.74
2	F_s, G_s	505	0.73
3	F_s, G_s, E_s	504	0.35
4	F_s, G_s, E_s, D_s	504	0.18
5	F_s, G_s, E_s, D_s, P_s	503	0.11

The results illustrate that the number of bidders has a critical effect on the optimal bid and expected payoff. An increase in bidders reduces payoffs and optimal bids, confirming that, from a buyer's perspective (i.e., the auctioneer), having more bidders is always better. However, the added benefit diminishes as the number of bidders increases beyond five. In the case of sun oil, with an average of eight bidders, there should be more than sufficient bidders to bid away profits.[8]

Random Bidders

Participation of some bidders is random. Consequently, from a strategic perspective, the probability of underbidding a specific opponent should be weighted by the probability that an opponent submits a bid [as discussed in Monroe and shown in equation (5)].

Bid distributions without adjustments for the random bidding are shown in figure 2, and figure 3 graphs the bid distributions with the adjustments included. Random participation in bidding essentially puts a lower bound on the probability of underbidding an opponent at the probability that the opponent does not compete. For example, the historic probability of D_s bidding was 0.69. Hence, any bid would underbid D_s with the probability of 0.31. After adjusting for random bidders, the lower end of the joint probability shifts rightward for high bids, but not by much. Before the adjustment, a bid above $505/mt had no chance of winning; now a bid up to $510/mt has a slight chance of winning.

Effects of Information on Bid Strategies

Information about rivals' costs and bidding behavior has an important effect on bidding strategies. Indeed, one of the interesting areas of competition relates to the role of information[9]—both from a bidder's perspective (i.e., in formulating strategies), as well as from an importer's (or auctioneer's) perspective (i.e., to the extent of revealing information about bids to competitors, or reducing informational uncertainties).[10] Of particular

[8] However, for the other oils, the number of bidders is often less than four, indicating that in some tenders, competition would be less intense (Wilson and Diersen). This disparity is a major theme of the evolving literature on procurement strategies and auctions, and on the role of the number of suppliers (see Brown, and McAffee and McMillan 1987, for further discussions).

[9] See Phlips; Dutta; Rasmusen; and Besanko, Dranove, and Shanley for examples of recent literature on this topic. Caves (1977–78) and Wilson and Dahl (1999) provide discussions of the role of information in the international grain trade.

[10] Specifically, buyers may or may not release results of tenders, which bidders can use to refine estimates about rivals' bidding strategies. McMillan (1992, p. 142) discusses the importance of the auctioneer revealing information.

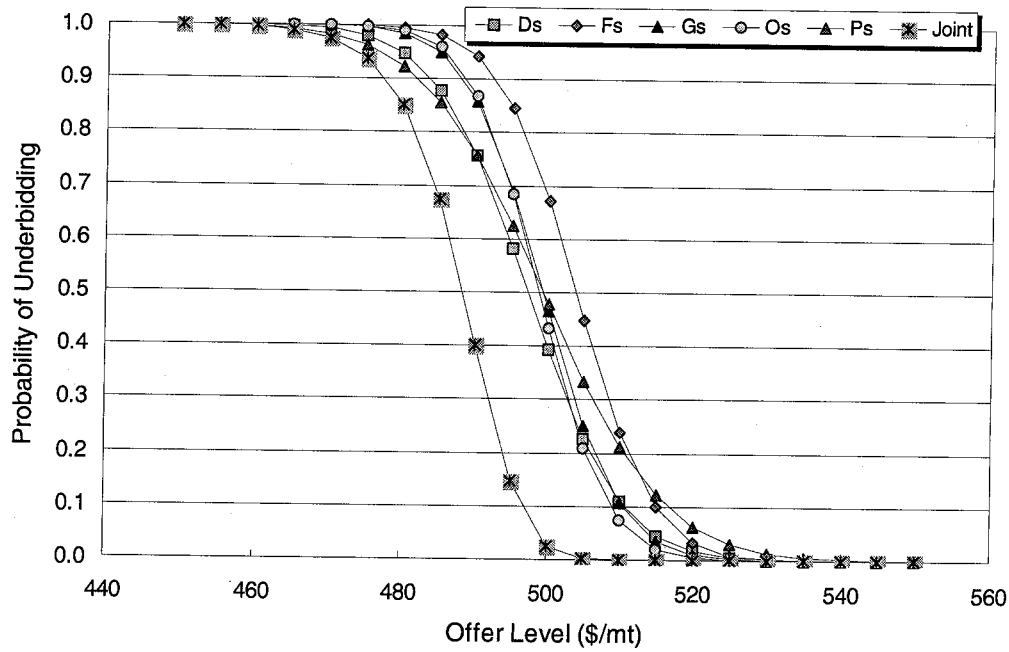

Figure 2. Bid distributions for sun oil without adjustments for random bidding

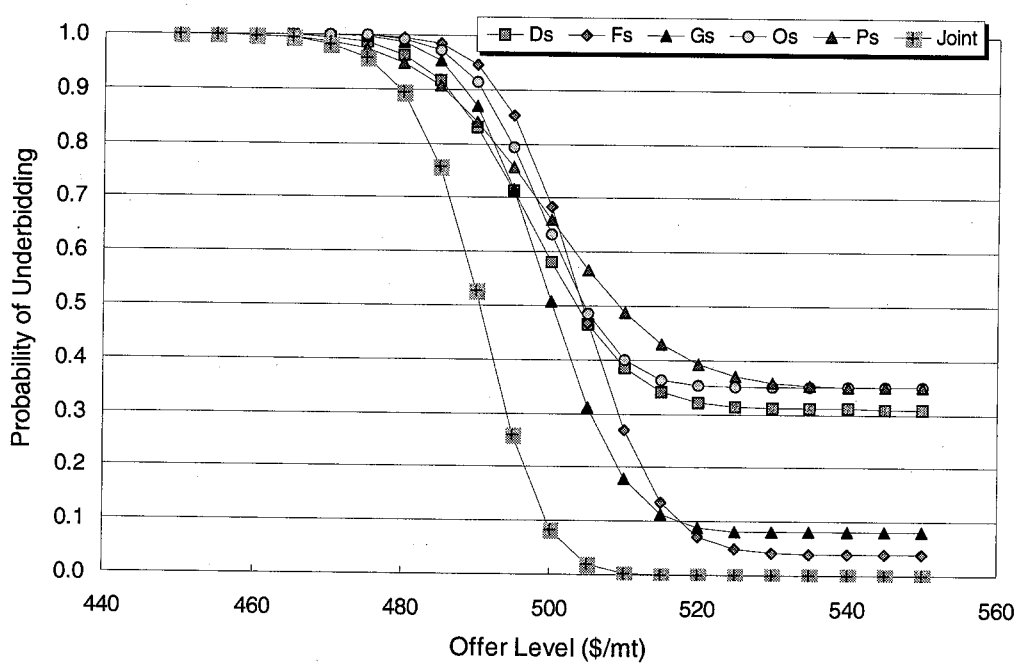

Figure 3. Bid distributions for sun oil with adjustments for random bidding

Table 4. Impacts of Informational Uncertainties on Optimal Bids: Low- and High-Cost Firms ($/mt)

	Cost (C_k) = $490/mt				Cost (C_k) = $500/mt			
	Optimal Bid		Expected Payoff		Optimal Bid		Expected Payoff	
N (competitors)	$\delta = 1$	$\delta = 2$	$\delta = 1$	$\delta = 2$	$\delta = 1$	$\delta = 2$	$\delta = 1$	$\delta = 2$
2	498	502	3.61	3.24	505	509	0.73	1.26
3	497	500	2.33	1.96	504	508	0.35	0.64
4	496	499	1.75	1.30	504	507	0.18	0.34
5	495	498	1.30	0.89	503	506	0.11	0.21

importance is the extent to which information about competitors' past behavior affects rivals' bidding strategies. As illustrated above, the effect of information is highly dependent on whether the firm is a high- or low-cost firm, as well as on the number of competitors in the tender.

To analyze these effects, the SER was used as the measure of information about bidders' strategies (i.e., the predictability of bid distributions). Let δ be a scale factor equal to 1 in the base case, and equal to 2 in the case representing less precise information. To evaluate the effects of informational uncertainties, we derive $\delta \times SER_i$. Optimal bids are then derived for two levels of information and for each of several numbers of bidders. The effect of information on the optimal bid is highly dependent on whether the bidding firm is high or low cost. Thus, we derive optimal bids for each of two costs: C_k = $490/mt and C_k = $500/mt, with the cost indicator for all rivals set at C = $500/mt.

Results are reported in table 4 and demonstrate that increasing δ increases the optimal bids in all cases. For a low-cost firm [with a higher $W(B)$], the $W(B)$ decreases, but not by enough to compensate for the effect of the increased bid. The expected payoffs decrease for a low-cost firm in a bidding situation with less information. For a high-cost firm [low $W(B)$] the opposite occurs. That is, the optimal bid increases, but the $W(B)$ is such that the expected payoff increases. In general, an increase in δ (i.e., an increase in informational uncertainty) lowers the expected payoff for the low-cost firm but raises it for a high-cost firm. Thus, less information among rivals raises (reduces) the expected payoff for high- (low-) cost firms.

These results have important implications for bidders and importers. Increases in the SER for all competitors have the effect of increasing the expected bid. For buyers, higher payoffs to bidders and higher optimal bids are undesirable. Thus, buyers should adopt mechanisms to reduce the SER (i.e., by releasing more information on bid results) to decrease uncertainty among bidders and intensify bidder competition. When this occurs, a low-cost firm would be favored with higher expected payoffs. For low-cost firms, greater certainty about competitor bidding is desirable, resulting in greater expected payoffs.

Summary and Conclusions

Auctions and bidding play an important role in agricultural marketing. A common and noteworthy application of auctions and bidding is that of import tenders, which are used for both pricing and allocation of purchases among sellers. In this study, we develop a model to evaluate bidding strategies and competition in Egyptian oilseeds imports.

The results are particularly interesting in understanding sellers' bidding strategies, competition among rivals, and impacts of specific variables on optimal bids and expected payoffs to sellers. Although this analysis is applied to a particular set of detailed data, the approach and implications are applicable in other bidding situations in agricultural marketing and contribute to an understanding of bidding strategies and competition.

The conventional analytical approach to bidding strategies is enhanced in this study by using Bayesian predictive density functions. Bid functions were estimated relative to expected costs. This approach differs from conventional approaches in which bid distributions are computed relative to own-costs and behavioral relationships are ignored. Bid functions are employed to compute specific distributions that can be used either as priors or updated to incorporate more bidder-specific information. Bayesian predictive densities also account for rival-specific information in the sample. As more bids are observed for a specific bidder (n for each bidder), the spread of the bid distribution decreases.

An additional benefit of this approach is that it accounts for different levels of costs. There was substantial fluctuation in the range of observed bids during even this short sample period, especially from bidders who bid infrequently. The predictive density accounts for differences between the current level of cost and its mean. Hence, if cost moves outside of historical ranges, the predictive density would be wider to account for that uncertainty in the sample.

Detailed data about the tendering for sun oil by Egypt were used in this study. Generally, the bids could be explained with a relatively high degree of confidence using simple relationships and accessible data. Several interesting characteristics emerged from the results. There appeared to be groups of bidders characterized by differences in their bid functions. This finding indicates rivals have fundamentally different bidding strategies likely dependent on their fixed and variable costs. Second, some bidders were highly predictable, both with regard to their bidding behavior and their participation in each tender. Other firms were less predictable.

Taken together, these statistical characteristics have important effects on formulation of bidding strategies, determination of optimal bids, and expected payoffs for the bidders. The number of rivals is very important. An increase in the number of rivals has the effect of decreasing optimal bids, and lowering prices for buyers. The frequency of random bidders in tenders has an important impact on results. In general, the incidence of random bidders puts a lower bound on the probability of underbidding an opponent, and has the effect of increasing the optimal bid. Information among rivals about competitor bids has an important impact on bidding strategies and expected payoffs. This effect depends on whether the firm is high or low cost. In all cases, less information about rivals' behavior raises bids. However, the effect of information differs across firms. Greater uncertainty about bidder behavior reduces expected payoffs for low-cost firms, but raises them for high-cost firms.

There are several important implications for participants in auctions. Buyers benefit from using auctions as a means of identifying low-cost suppliers. The benefits increase, resulting in lower prices, if there is an adequate number of bidders and if they bid routinely. Benefits can be further enhanced by releasing information to rivals that would allow them to better depict rival behavior. For sellers in these types of auctions, the methodologies can be used to formulate bidding strategies. Finally, the Bayesian

approach is appealing relative to conventional approaches because it incorporates behavioral relationships for past tenders in derivation of probabilities of winning against rivals using accessible information.

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