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Competitive Bidding on Import Tenders: The Case of Minor Oilseeds

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TABLE OF CONTENTS

List of Tables

List of Figures

HIGHLIGHTS

Auctions and bidding play an important role in agricultural marketing. A common and noteworthy application of auctions and bidding is that of import tendering which is used for both price determination 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 for understanding sellers' bidding strategies, competition among rivals, as well as impacts of specific variables on optimal bids and payoffs to sellers. Although this analysis is applied to a particular set of detailed data, the approach and implications have many applications in other bidding situations in agricultural marketing and provide a contribution to understanding bidding strategies and competition.

This study used detailed data from tendering by Egypt for three vegetable oils (sun, cotton and palm). Bid functions were estimated for each supplier for each oil. Results indicated that generally, bids could be predicted for all bidders with a relatively high degree of confidence using simple relationships and accessible data. However, for each oil there appeared to be groups of bidders characterized by differences in their bid functions.

Taken together, bid functions have important effects on formulation of bidding strategies, on determination of optimal bids, and on expected payoffs for bidders. The bidding model was used to examine the effects of these and other variables on the auction results. Results indicated:

- The number of rivals affects the results in a predictable way. An increase in the number of rivals decreases optimal bids, and lowers import prices for buyers.

- The frequency of random bidders in tenders has an important impact on the results. In each oil there were several bidders that did not bid in each tender, resulting in uncertainty in the number of bidders in a particular auction. The incidence of random bidders essentially places a lower bound on the probability of underbidding an opponent and has the effect of increasing the optimal bid.

- Information among rivals about competitor bidding strategies has an important impact on bidding strategies and expected payoffs. However, the magnitude depends on whether the firm is high or low cost relative to its competition. Results indicate that, in all cases, less information about rivals' behavior has the effect of raising bids.

ABSTRACT

Auctions and bidding play an important role in agricultural marketing. A common and noteworthy application of auctions and bidding is that of import tendering which is 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 in Egyptian oilseeds imports.

Information included the values of bids submitted by each supplier in each tender over the period 1990 to 1993. Results indicate that generally bids could be predicted for all bidders with a relatively high degree of confidence using simple relationships and accessible data. In addition, for each oil tender there appeared to be groups of bidders characterized by differences in their bid functions.

The results are particularly interesting for understanding sellers' bidding strategies, competition among rivals, as well as impacts of specific variables on optimal bids and payoffs to sellers. Although this analysis is applied to a set of detailed data, the approach and implications have many applications in other bidding situations in agricultural marketing and contributes to understanding bidding strategies and competition.

Keywords: Bidding, Auction, International Grain Competition, Grains, Importing

COMPETITIVE BIDDING IN IMPORT TENDERS: THE CASE OF MINOR OILSEEDS

William W. Wilson and Matthew A. Diersen*

Introduction

Bidding competition plays an important role in many aspects of agricultural marketing. It has two main functions: pricing and allocation. Transaction prices are discovered through bidding competition and allocations are made among suppliers. Alternatives to bidding are other forms of pricing, including negotiation and posted prices. Because of the efficiency of bidding competition in fulfilling these roles, it is used in numerous commodities, products and services in general commerce and the agricultural marketing system. Recent examples in the commercial sector range from spectrum rights to airwave auctions, and numerous forms of internet-based auctions. Examples in the grain marketing industry include bidding for forward cash contracts, import tenders, allocation of EEP subsidies, and allocation of CCC owned stocks. More recently, bidding has been adapted in rail service (Wilson, Priewe, and Dahl).

One of the conventional uses of bidding competition is in tenders held by importers to determine suppliers for grains, oilseeds and related products. Similar processes are used by domestic buyers, but to a lesser degree of formality. The popularity of this form of competition in import tenders is likely related to the large volume and value of the commodity being procured, where small deviations in price have a great impact on total cost. Another reason is that importers have uncertainty in the value of marketing costs, which vary through time among and across potential exporters, making *a priori* selection of an individual supplier somewhat tenuous. The final reason is that in many cases there are institutional mechanisms prescribing a tendering process. Examples include administration of export programs, international financing arrangements, and internal import control mechanisms (e.g., exchange controls) in some countries. More recently, as part of the deregulation of imported feed grains in Japan, the importers have adapted a tendering system (Rampton).

There are several important and interesting questions about the execution of bidding programs of particular interest to importers and exporters in the international grain and oils trade. These are: 1) identification of bidding strategies used by competitors: 2) determination of optimal bids; 3) the effect of the number of bidders on bidding competition; and 4) how information affects bidding competition among participants. These are all questions frequently raised by market participants and have not been addressed in the agricultural economics literature.

This paper develops a model of bidding competition that can be used to analyze strategies of competitors and effects of crucial variables on auctions. It builds upon recent advances in

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auction theory and bidding. The model is applied using actual data from Egyptian import tenders for three vegetable oils (sun, cottonseed, and palm) bought on the international market. The first section provides a review of previous studies on bidding models. The second section presents a statistical analysis of the Egyptian oilseeds import tenders. The bidding model and factors affecting optimal bids are discussed in the third section. Of particular interest is the effect of the number of bidders and information on bidding strategies. Also there are interesting differences in the competitive structure across the three oils which are revealed in their bids.

Analytical Models of Bidding Competition

Related Literature

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

These mechanisms have come to be in vogue in recent years as procedures for allocating assets in certain industries following deregulation [Shebl; Kuttner; McMillan (1994); McAfee and McMillan (1996a)] and have been revered in popular magazines (Norton; *Economist*). Indeed, there have been numerous recent studies that have applied these techniques. Examples include: Crampton (1995); Hendricks and Porter; Hendricks, Porter and Wilson; and McAfee and McMillan (1996a, 1996b). Recent examples in agriculture are summarized in Sexton (1994b, pp. 189-95) and include analyses of EU export tenders [Borgeon and LeRoux (1996a and 1996b)], price transparency (Wilson, Dahl, and Johnson) and the Conservation Reserve Program (Latacz-Lohmamm and Hamsvoort). An important distinction needs to be made regarding the analytical models used to study auctions. A strain of the literature (e.g., Lilien and Kotler; Engelbrecht-Wiggans; Rothkopf and Harstad) use decision models based on the individual decision maker's strategy, taking competitor's strategies as given. This is the approach developed in this paper and follows other related research analyzing strategies of individual players (e.g., Capel; Crampton).

This paper models decisions of individual bidders and uses empirical data to derive expectations of competitor bids which are incorporated into the bidding strategy. The oilseeds auctions are distinct when considering the strategies for formulating bids. In the oilseeds auctions, the disparity across bidders in terms of their geographic locations, supply conditions at origination sites, inventory, and logistics positions leads to different cost structures that need to be accounted for in bidding strategies. Results from the three oils provide interesting comparisons of different competitive structures on bidding strategies.

Theoretical Model

A bidder's objective is to maximize expected payoffs associated with alternative bids. The objective function is defined as: $E(\pi) = (B - C) \cdot P(W)$ where $E(\pi)$ is the expected payoff, B is the bid, C is cost and P(W) is the probability of underbidding. The crucial variable is P(W), the probability of underbidding all other bidders.

Conventional Approaches Monroe, Lilian and Kotler, Nagle (and others) demonstrate various approaches to deriving P(W) which ultimately are used in derivation of optimal bids. These include what are referred to as the winning bid approach, the average opponent approach and the specific opponent approach. Applicability of different approaches ultimately depends on the form and availability of information. In all cases, some measure of own and/or opponents' costs have an effect on chosen or optimal bid values.

The approach closest to that used in this study is the *specific opponent approach* (Monroe; Nagle and Holden pp. 203-204) where information exists on past bidding behavior of individual bidders. Procedures conventionally prescribed for determining P(W) in the specific opponent approach are: 1) assess competitor bids as a percentage of own cost on past bidding occurrences; 2) categorize these in discrete intervals; and 3) compute the fraction of each competitor's previous bids which exceed B. This is interpreted as the probability that B is less than the competitor's bid for each bidder j, P_j (W). This approach is a discrete method for computing the probability of underbidding an opponent using own costs as a reference. It can be expanded to handle multiple and random opponents (i.e., those that randomly compete in each tender).

Lilien and Kotler (pp. 424-428) show a continuous method for determining the bid distribution. The procedure can be adapted to handle multiple opponents and an uncertain number of "common" bidders. Their procedure involves:

1) Computing the ratio $r_j = O_j/C$, of an opponent's past bid, O_j, to own cost, C;

2) Derive the bid distribution g_j (y), where y is opponent j's bid, to compute the probability that j's bid exceeds own bid:

$$\int_r^\infty g_j(y)dy, \text{where } r = O_j/C; \tag{1}$$

3) With multiple opponents separate distributions are derived for each and the product of the probabilities is used to derive the probability of winning; and

4) With uncertainty in the number of opponents, who share a common bid distribution, the joint probability can be weighted by the number of expected bidders.

Important factors affecting bidding competition are the number of competitors, how consistently they bid, and their bid distributions. Analysis of past bidder behavior provides insight into who bids and when they bid. Analyzing past behavior also gives insight into future bid distributions of different bidders. The approaches described above share the common theme that competitors' bid distributions are based on (or derived from) known and common costs. However, the assumption of common costs across all bidders is difficult to justify in most international agricultural markets.

Bayesian Transformation Bayesian analysis can be used in formulating bidding strategies.[1] There are two motivations for using Bayesian statistics as an alternative for determining competitors' bid distributions. One is that other methods rely on own or competitors' costs, which in practice are not observable at the time of bidding. The other motivation is the common practice of releasing auction results ex post. Such information can be used to generate bid functions and probability distributions of potential bids.

Bidders can use past bidding behavior to model the expectation of bids, E(B), and to derive the probability of winning the tender, P(W). Given that costs are not observed, a proxy for costs can be used to predict bid distributions using a bid function. Regression is used to estimate bid functions for specific bidders.[2] Of particular importance is the relationship between an opponent's prior bids, B_{jt}, and a cost indicator C_t. A bid function for a specific bidder is specified as:

$$B_{jt} = \alpha_j + \beta_j C_t + \varepsilon_{jt}, \tag{2}$$

where ε_{jt} is $N(\mu, \sigma^2)$. The bid function is used to predict bids by conditioning on a current indicator value, C_t^*. The expected bid, B_{jt}^*, for competitor j is:

$$B_{jt}^* = \alpha_j + \beta_j C_t^* \tag{3}$$

Knowing the bid function can be used to derive the expected bid and is useful for understanding bidder behavior. However, knowledge of the entire distribution of a competitor's bid is necessary for determining $P_j(W)$. The Bayesian approach uses sample information and prior beliefs to determine the entire distribution of the dependent variable (Press). A bidder can use prior knowledge, a sample of past bids and a new observation of C_t to compute the predictive density for any potential bids for bidder j.

With a naïve prior, the difference between any potential bid and the expected bid, when standardized, follows a t-distribution. This relationship is derived as:

[1] Kennedy (pp. 208-209) explains the subtle attributes of Bayesian analysis and contrasts it with non-Bayesian probabilities.
[2] Use of bid functions has recently been discussed and used in analyzing bidding strategies in experimental auctions in Avery and Kagel (pp. 588-589).

$$\frac{B_{jt} - \alpha_j - \beta_j C_t^*}{\hat{\sigma}\sqrt{1 + \frac{1}{n_j} + \frac{(C_t^* - \bar{C})^2}{\sum_1^{n_\varphi}(C_t - \bar{C})^2}}} \Bigg| \text{sample} \sim t_{n_\varphi - 2} \tag{4}$$

where B_{jt} is any potential bid from bidder j, C_t^* is the current cost indicator value, C_l is the subset of cost indicator values that correspond to bids observed for bidder j, $\hat{\sigma}$ is the standard error of the regression for bidder j and n_j is the number of observations for bidder j. Any potential bid can be mapped to a t-value and then a probability. The procedure for arriving at predictive density values is discussed later. The predictive densities are bidder-specific. Hence, the sample size, standard error, and mean cost indicator level are relative to the history of a specific bidder, not to the group of all bidders.

The above relationship shows that the predictive density depends on three important parameters. The first term in the denominator, $\hat{\sigma}$, is constant, which implies its effect is independent of the number of observations. Uncertainty of an opponent's behavior thus remains and limits the precision of the density estimates. The effect of the second term in the denominator becomes smaller with an increase in the number of bids, n_j. The density is also influenced by any deviation from the mean cost indicator level. The predictive distribution results are similar to the derivation of confidence intervals in classical regression due to assumptions that the disturbances are normally distributed, the prior distribution is uniform (reflecting an ignorance of it), and the loss function is symmetric (Kennedy).

Derivation of optimal bids

Bidder-specific samples are used to predict densities for different offers of rival bidders. Different probabilities are associated with t values, which represent the probability of the specific opponent bidding at or below that offer level.

Using this information, an optimal bid can be determined. First, the probability of underbidding each opponent, P_j (W) across a range of potential bids, is derived. Then, the joint probability of underbidding all opponents $P(W) = P_1(W) \cdot P_2(W) ... P_N(W)$ is computed [i.e., $P(W) = \prod(P_j(W))$]. These probabilities are used to determine the optimal bid, or the bid yielding the highest expected payoff, defined as $E(\pi) = (B - C) \cdot P(W)$. In a special case where an opponent does not bid in each tender, the probability of winning becomes $P_j'(W) = p_j \cdot P_j(W) + (1 - p_j)$ where p_j is the probability the competitor bids.

The functional relationships affecting determination of the bid are illustrated in Figure 1. Higher bids result in a greater payoff, but also a lower probability of winning. The product of

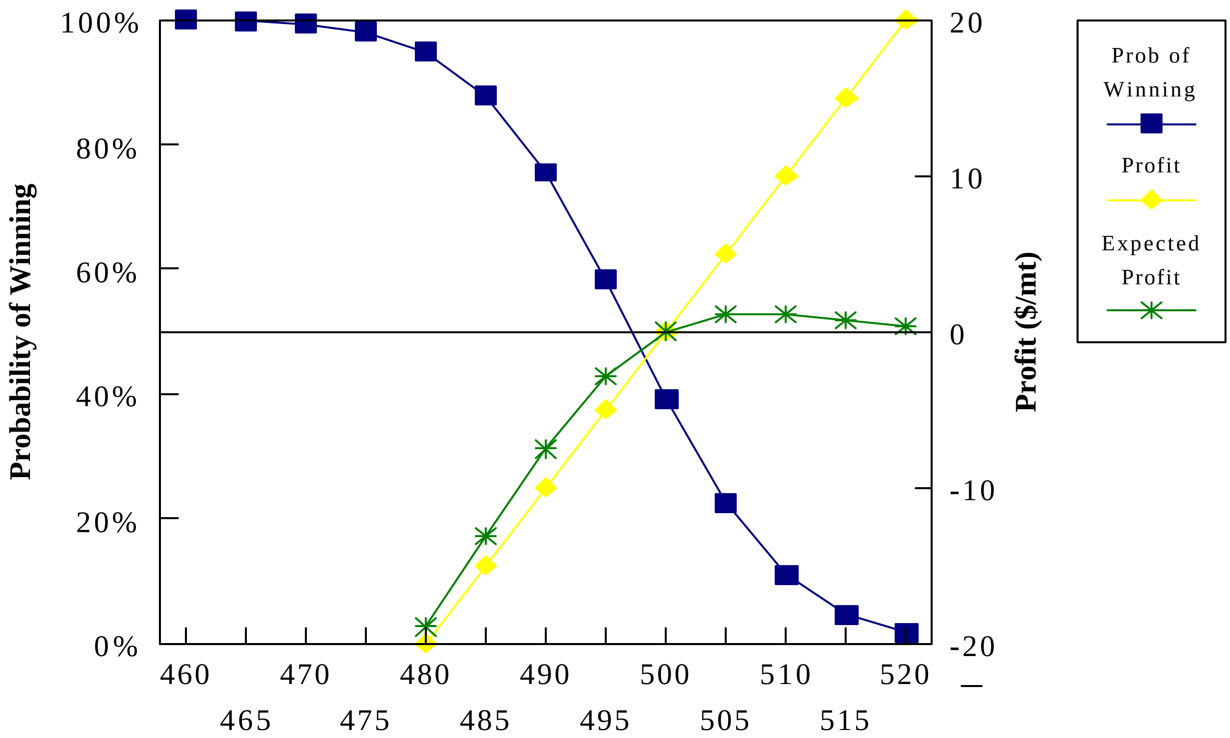

Figure 1. Derivation of Expected Payoffs and Optimal Bid

these two functions yields the expected payoff, E(π). The bid value associated with the maximum of that function is the optimal bid. Deviations from this bid would affect both the probability of winning and the payoff, and would result in a lower E(π). An important parameter affecting bidding competition is the number of bidders, the effect of which is elaborated in the empirical analysis. Reduction in the number of bidders increases P(W), and as a result, the optimal bid increases as does the E(π).

Statistical Analysis of Competitor Bidding in Minor Oilseeds

Data Sources

A data set was developed from all tenders received by the Egyptian procurement agency responsible for importing vegetable oils. Tenders for these oils were generally held monthly and were at about the same time each month. Tender terms asked for bids for one to three different vegetable oils (sun, cottonseed and palm). The time period for the analysis presented here covers all tenders from January 1990 through August 1993. Suppliers are exporting firms, some being both the processor and exporter, others being processors' agents. Some suppliers bid on each of the oils being tendered, others would offer on only one oil. Sometimes suppliers make multiple offers at different bids (i.e., scaled bids)[3] which is a common practice in international tendering. In our case these were each treated as separate offers by that particular supplier.

Table 1 shows summary statistics for the tenders. There were twenty-six tenders for sun oil. Over the three-year period twenty different firms submitted bids in sun oil tenders. The number of firms submitting bids, or suppliers, varied over time as does the number of bids each submitted. Thus, for each tender the number of bidders and the number of total bids varied. The number of bids exceeds the number of bidders because of multiple bids. For any one tender, the maximum number of separate bidders was eleven. There were fewer suppliers in the cottonseed and palm oil tenders. Palm oil was seldom tendered with only 51 bids in 7 tenders. The average number of bidders was comparable to the cottonseed tenders at 4, with an average of 7 bids per tender.

A time series of alternative cost indicators was used and values derived which corresponded to each tender date. The indicator values included: Rotterdam prices for soybean, palm, sun, and rapeseed oil; FOB New Orleans sun oil; CBT soybean oil and the equivalent of the FOSFA index.[4] These are taken to selectively represent the time series variability in costs of rivals that are not observable by competitors. Bid functions were estimated to determine the indicator that which most accurately describes their bidding behavior.

Table 1. Characteristics for Egyptian Oilseed Tenders

	Sun	***Cottonseed***	***Palm***
Number of Tenders	26	24	7
Bidders			
Total firms submitting offers	20	12	9
Average firms per tender	8	3	4
Maximum per tender	11	6	7
Offers			
Total	397	145	51
Averaged across tenders	15	6	7

[3]For example, one supplier made the following offers for a particular Sun oil tender: 5,000 mt @ $476.00/mt; 5,000 mt at $476.50/mt; and 10,000 mt at $477.00/mt.

[4]A CBOT index of specialty oilseed prices traded for a short period of time.

Statistical and Graphical Analysis

Sun Oil Tenders Figure 2 shows the number of bidders and total bids over time for the 26 sun oil tenders. The number of bidders and total bids fluctuate across tenders. The fact that there were more bids than bidders on a particular tender reflects that some bidders submitted multiple offers. Figure 3 shows the time-series of bid distributions for each tender as well as the mean. Bids on each tender appear to be bunched in the middle with bids tailing toward the high end of offers. Most "outlier" bids appear to be gathered at the high end of the bids suggesting some bidders may be using a strategy of high payoff and low probability of winning.

A boxplot of the bids across tenders is shown in Figure 4.[5] The plot demonstrates the disparity across tenders. The size of the boxes and tail lengths change from tender to tender, indicating that bidders as a group behave differently from tender to tender. Tall boxes and long tails indicate a high variance across bids (for example, compare tenders 2 and 4 to tenders 1 and 3). Long tails relative to box height indicates disparity across bidders (for example, tender 2). A long tail on the bottom suggests the winner's curse, or underpricing the winning bid (for example, the third from last tender).

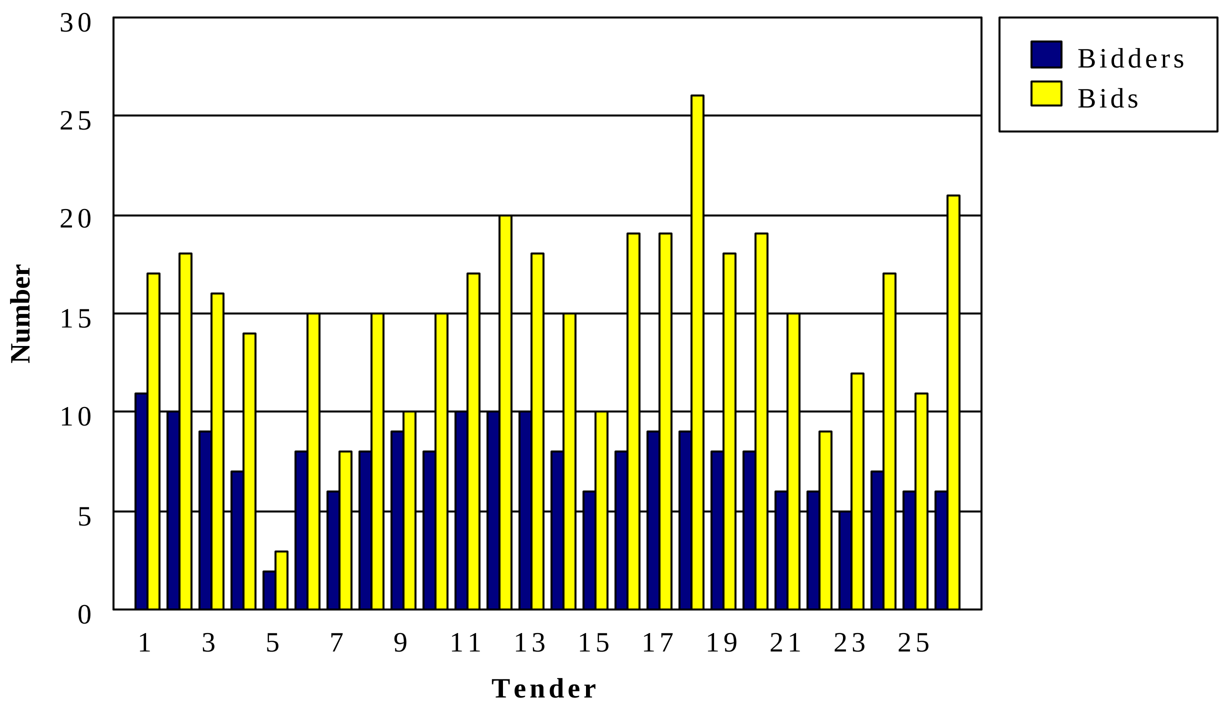

Figure 2. Sun Oil Tenders: Number of Bids and Bidders by Tender

[5] Boxplots show the minimum and maximum bids as the end of the tails. The "box"contains the second and third quartile (50% of the observations lie within the box), with the line in the center showing the median (middle) bid.

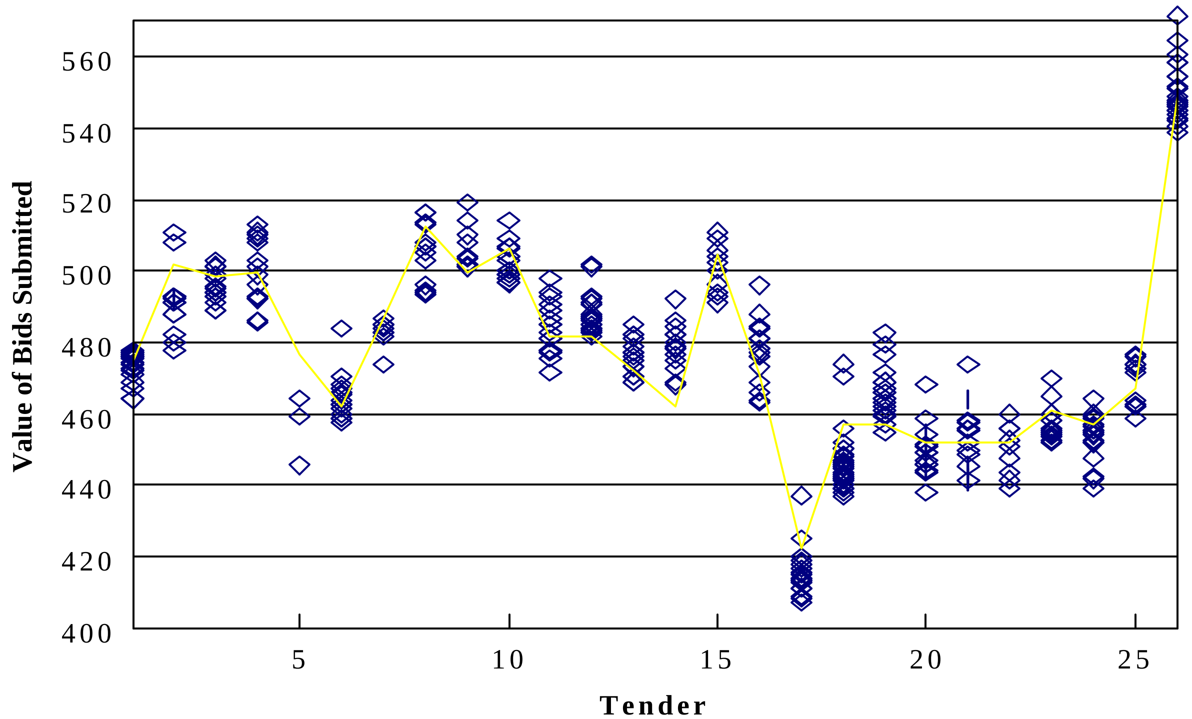

Figure 3. Sun Oil Tenders: Value of Bids

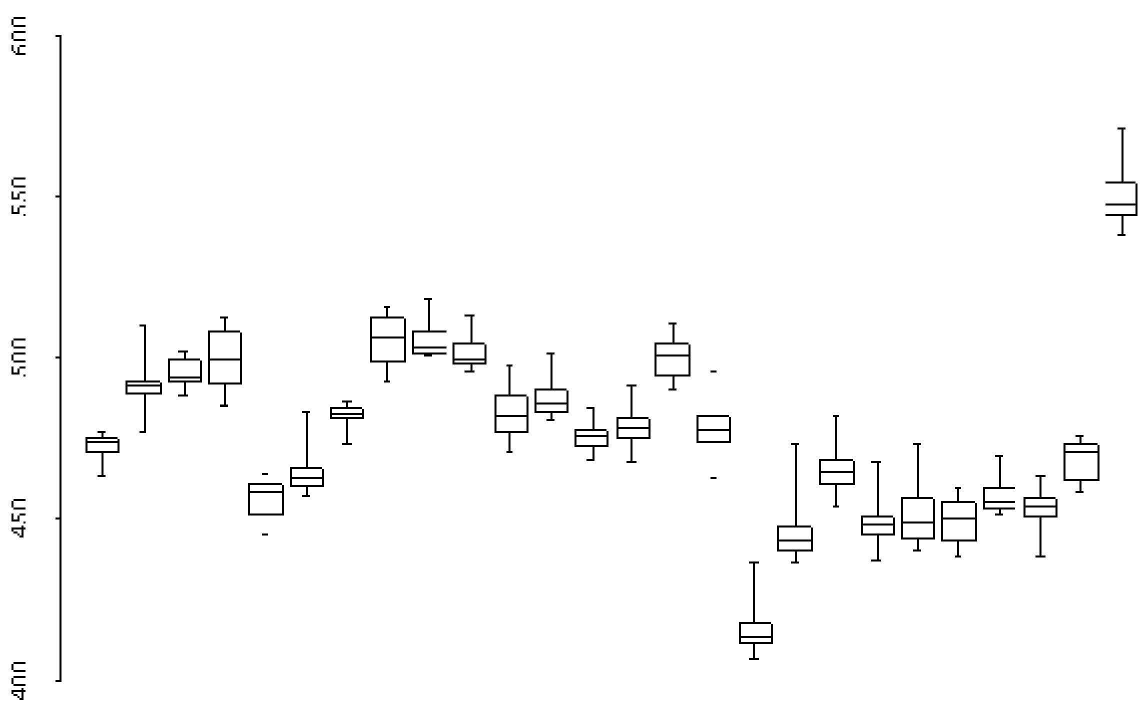

Figure 4. Sun Oil Tenders: Boxplots of Bids Across Tenders

Figure 5 shows a similar boxplot of deviations from the indicator value, $M_{jt} = B_{jt} - C_t$ where C_t is the relevant indicator cost (in this case Rotterdam Sun Oil). There was substantial variability both in the mean and variance of M_{jt} suggesting the extent to which the implied gross margins reflected in the bids vary. Results of a one-way ANOVA show that the deviations across tenders, M_{jt}, are not constant. Some pairs of variances tested different as well. The means of M_{jt} were tested for equivalence. The F-statistic of 13.76 was sufficiently high to reject H_0 . These results confirm the visual evidence that the means (and variances) of gross implicit margins are statistically not equal. Standard deviations of the bids across bidders for each tender shown in Figure 6, are not constant. These suggest that uncertainty in bids changed across tenders, confirming the utility of using auctions to discover those suppliers with minimal costs.

Though costs for each bidder are unobserved, the value of the commodity at a common pricing provides a measure of the opportunity cost through time. The relation between the bids and C_t are shown in Figure 7.[6] A simple regression line is added and shows that many of the tenders have a majority of the distribution away from the predicted line. The value of the winning bids relative to the Rotterdam price are shown in Figure 8. Only accepted winning bids are shown and are usually below the Rotterdam price. At a Rotterdam price of $420/mt, for example, 3 bids were accepted and all are below that value. Deviations are expected as bidders have different transportation costs relative to Rotterdam, and Figure 8 also shows that Egypt normally buys at a discount to Rotterdam.

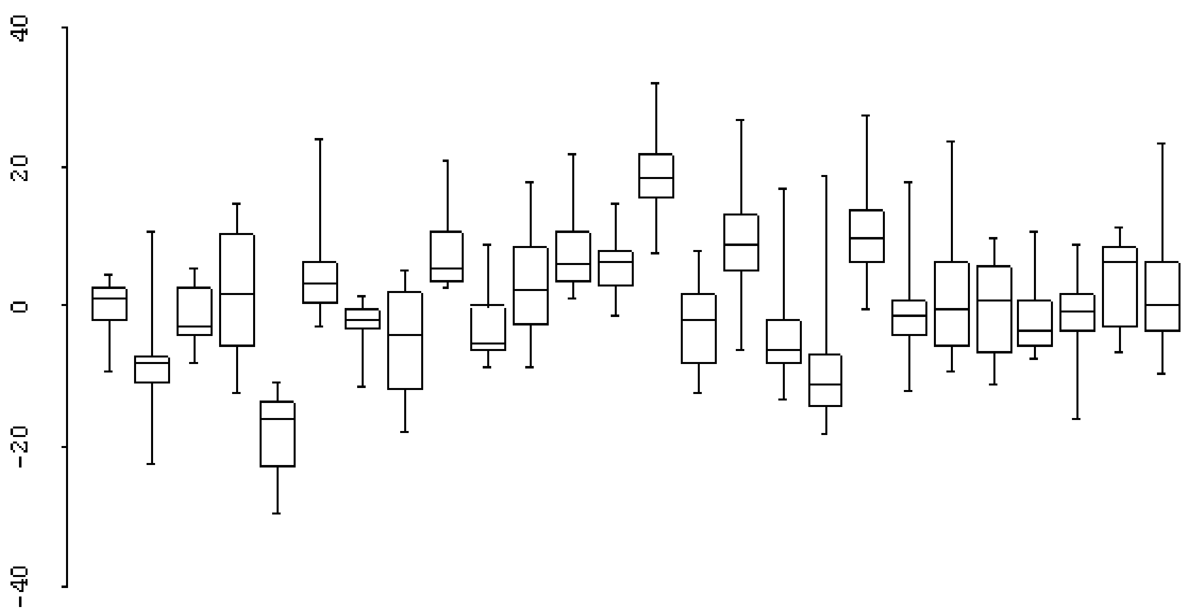

Figure 5. Sun Oil Tenders: Boxplots of Derivations of Bids From Cost Indicator Across Tenders

[6] The bids are plotted against the Rotterdam price on the date closest to the tender date and shown in Figure 7.

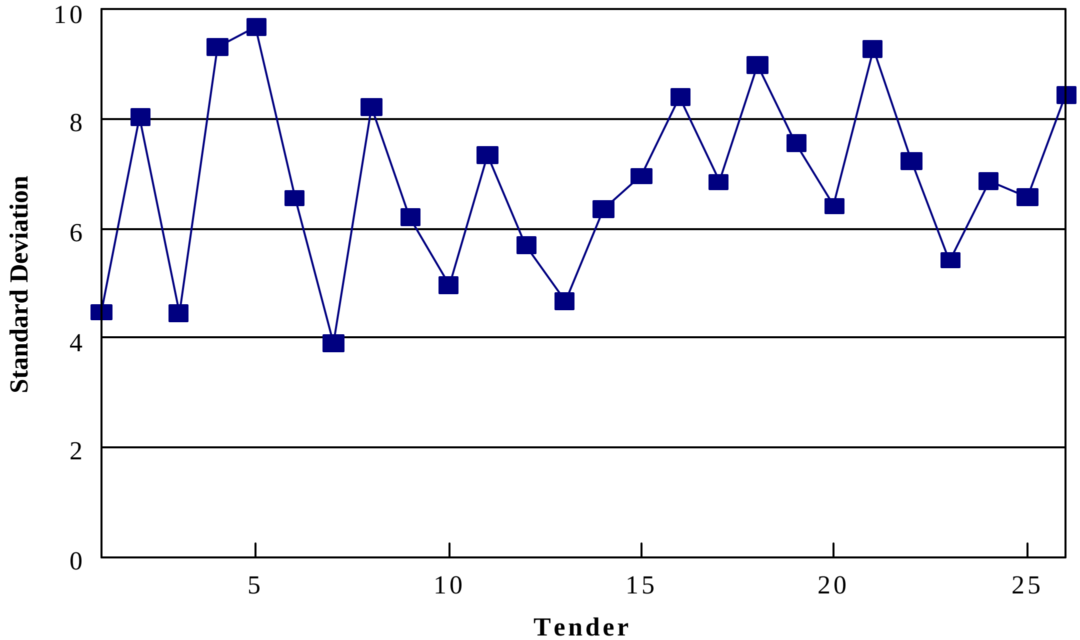

Figure 6. Sun Oil Tenders: Variation of Bids

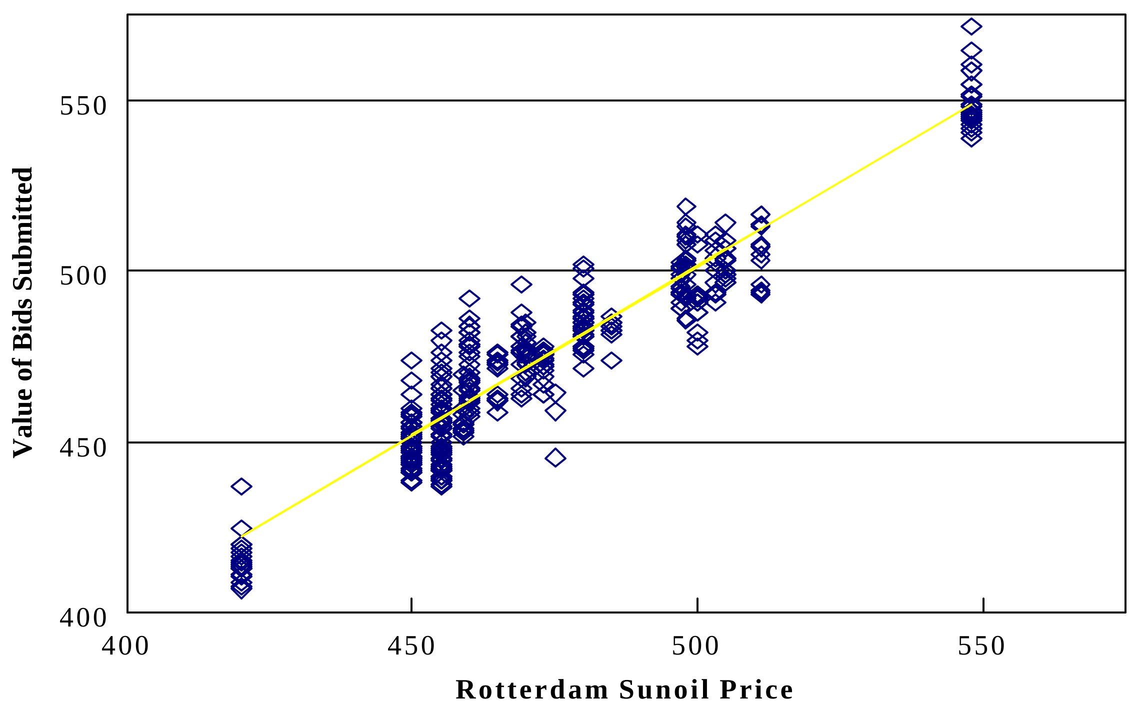

Figure 7. Sun Oil Tenders: Bids Relative to Rotterdam Sun Oil

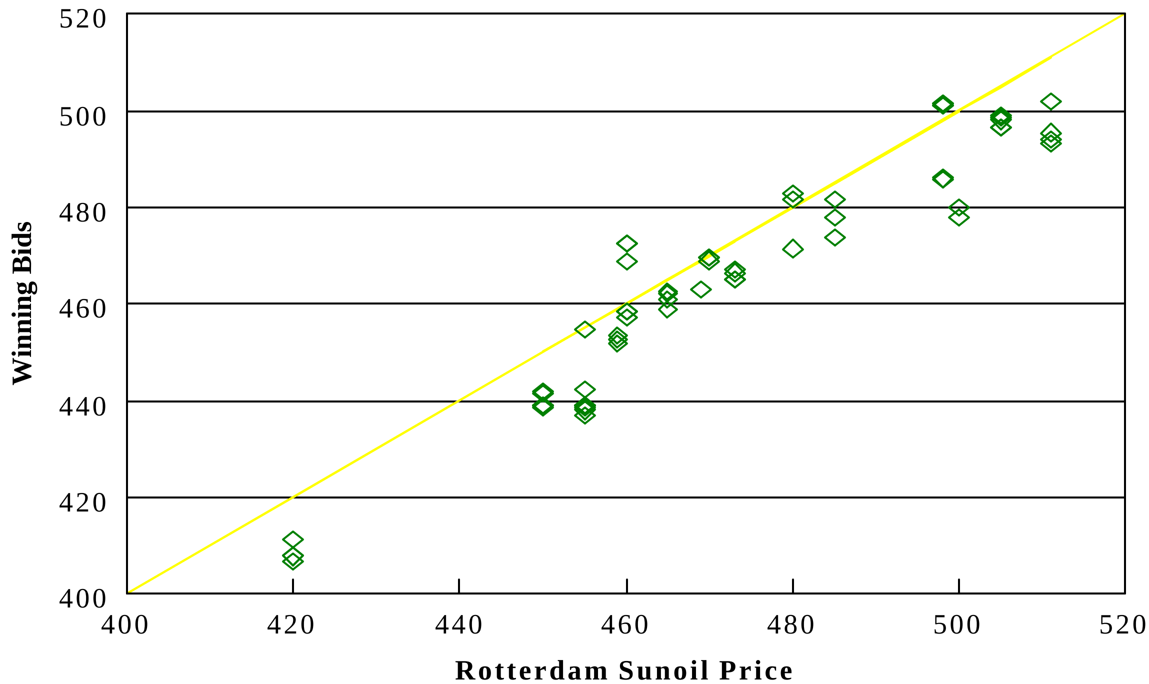

Figure 8. Sun Oil Tenders: Winning Sun Oil Bids in Relation to Rotterdam Sun Oil

Means and Variances Mean and variance of bids submitted by each of the individual suppliers are shown in Table 2. The number of bids ranged from a low of 1 to a high of 72. There were many sporadic bidders, and few submitted bids at each tender. Of those suppliers with more than 20 bids, bidder O_s has the greatest standard deviation of 38 and bidder B_s has the lowest at 20.

Another way to make comparisons across bidders is to use $M_{jt} = B_{jt} - C_{t,}$ where B_{jt} is the bid, C_t is the cost indicator and M_{jt} is the deviation from the indicator price. This isolates the effect of changes in C_t over time. A_s and R_s submit high bids, with an average of \$10.88 and \$11.00/mt respectively over Rotterdam. Other bidders were well below Rotterdam, such as L_s, Q_s and T_s. The variances of deviations from the normal spread are also shown. C_s, E_s, P_s, Q_s and R_s all have relatively high standard deviations, suggesting they are much more random in their bidding behavior; M_s and S_s, with lower standard deviations, are more predictable.

Cottonseed Oil Tenders Figure 9 shows the tenders for cottonseed oil. Compared to sun oil, there were fewer bids per tender. For both cottonseed and palm oils, the bids were submitted fewer in number, submitted by few suppliers, at a lesser frequency relative to the sun oil tenders. Means and standard deviations of cottonseed oil bids for each supplier are shown in Table 3. The number of bids ranges from 1 to 61, with the vast majority made by just 3 suppliers, A_c, C_c, and H_c.

Table 2. Sample Statistics: Sun Oil Bids

Supplier	***# of offers (bids)***	***Bid Value***		***Deviations from*** **C_t (M_{jt})**	
		Mean	Standard Deviation	Mean	Standard Deviation
A_s	4	476	28	11	8
B_s	25	466	20	4	9
C_s	17	464	31	5	11
D_s	37	469	29	-2	10
E_s	23	468	29	0	11
F_s	51	478	22	6	8
G_s	72	477	32	0	8
H_s	6	492	14	-2	7
I_s	10	487	17	1	7
J_s	28	504	35	2	8
K_s	8	478	24	0	10
L_s	1	439	-	-11	-
M_s	4	454	1	1	3
N_s	24	486	22	2	8
O_s	38	470	38	-2	8
P_s	34	482	20	3	10
Q_s	6	476	13	-4	11
R_s	2	465	13	10	13
S_s	6	451	5	1	5
T_s	1	464	-	-9	-

Note*:* Mean and variance are computed across tenders for each bidder.

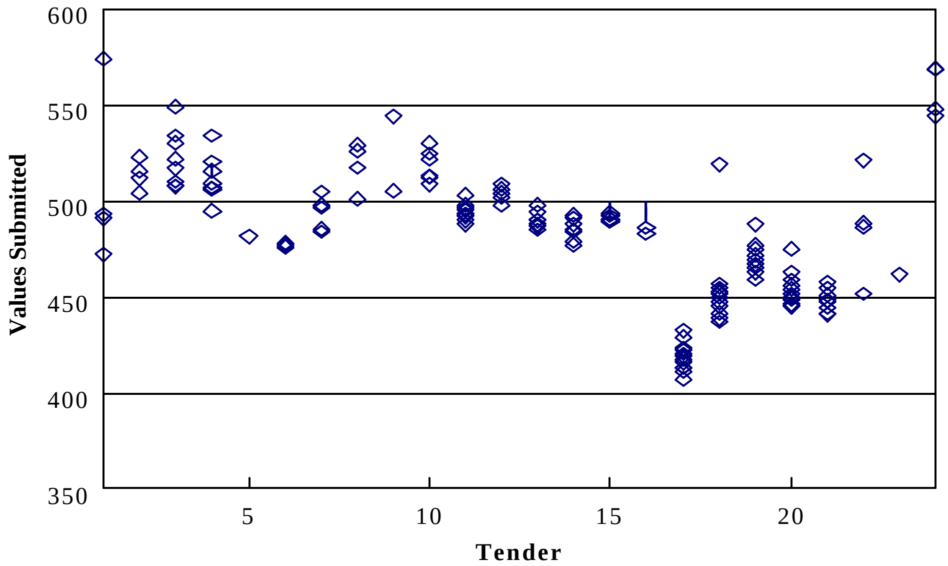

Figure 9. Cottonseed Oil Tenders: Value of Bids

Table 3. Sample Statistics: Cottonseed Oil Bids

Supplier	***# of offers (bids)***	***Bid Value***		***Deviations from C_t (M_{jt})***	
		Mean	Standard Deviation	Mean	Standard Deviation
A_c	13	494	36	30	24
B_c	7	518	8	14	8
C_c	61	481	35	10	11
D_c	1	534	-	37	-
E_c	2	490	20	18	3
F_c	8	502	13	12	8
G_c	5	516	29	30	15
H_c	38	465	33	2	13
I_c	2	495	1	-9	1
J_c	6	495	15	11	8
K_c	3	497	10	-1	9
L_c	3	508	21	43	38

Note*:* Mean and variance are computed across tenders for each bidder.

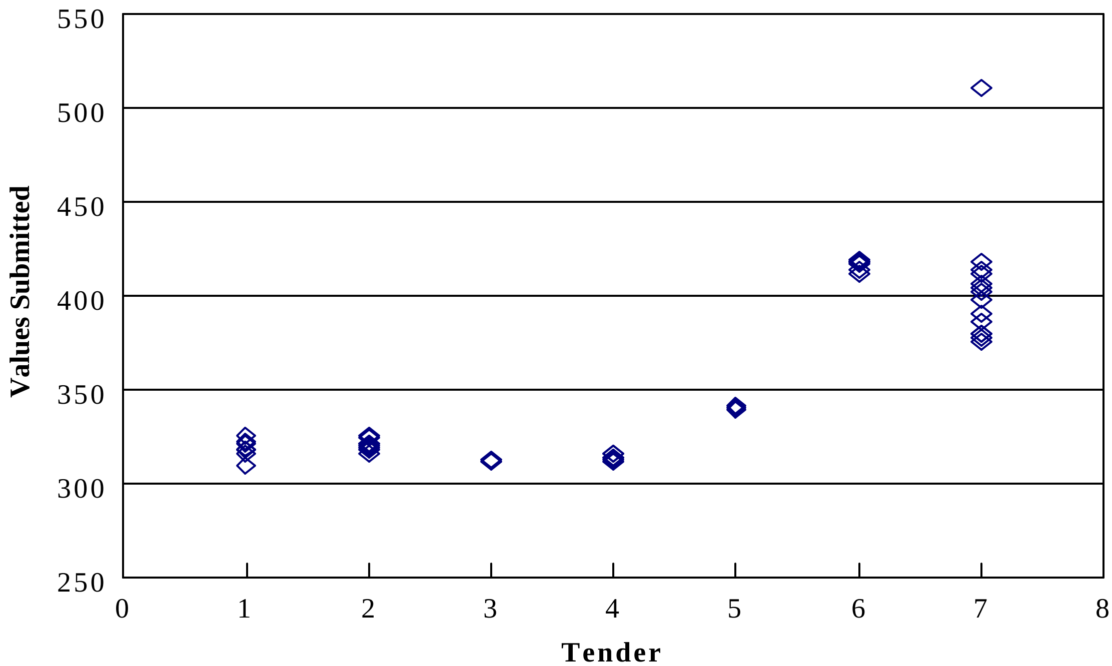

Figure 10. Palm Oil Tenders: Value of Bids

M was derived for each bid using Rotterdam sun oil.[7] Means and standard deviations are shown in Table 3. The lowest average bids (measured by M_{jc}) were submitted by I_c and K_c, but these suppliers submitted bids only 2 and 3 times respectively. The standard deviations for A_c, C_c, and H_c (the firms with the most frequent offers) were greater than those for most other bidders.

Palm Oil Tenders Figure 10 and Table 4 show comparable data for Palm oil tenders. Results illustrate that there were few tenders, with few firms participating in each tender. Two firms, G_p and E_p account for the majority of offers.[8] Compared to tenders for the other oils there was much greater variability in tender offers. The standard deviation in M tends to increase from sun oil to cotton and palm, likely reflecting impacts of fewer bidders as well as less liquidity in the latter two markets

[7]Several alternatives were available for cost indicators, C, for deriving M. To evaluate several regressions were estimated. The U.S. Gulf and Rotterdam cottonseed oil price were tested, with poor results: $R^2 < .31$. Rotterdam sun oil price provided a better fit to the data, $R^2 = .74$, and is used for comparing the suppliers. One bidder bid relatively infrequently and was lumped with the other small bidders and considered as a random entrant with an unknown bidding strategy

[8]Both the Malaysian palm and E.C. prices are correlated with the bids. Malaysian palm was chosen as an indicator because the individual supplier regressions fit better (shown later). Out of nine different suppliers only A_p, D_p, I_p, and G_p had sufficient bids for separate regressions.

Table 4. Sample Statistics: Palm Oil Bids

Supplier	***# of offers (bids)***	***Bid Value***		***Deviations from*** C_t (M_{jt})	
		Mean	Standard Deviation	Mean	Standard Deviation
A_p	6	396	16	60	12
B_p	3	319	5	46	4
C_p	1	318	-	43	-
D_p	5	350	51	51	16
E_p	9	358	48	56	16
F_p	3	448	55	115	55
G_p	18	348	40	55	14
H_p	3	418	1	75	1
I_p	2	323	3	48	4

Note*:* Mean and variance are computed across tenders for each bidder.

Bid Functions

Procedures Bid functions were estimated for each firm bidding on each type of oil. The general form was: $B_{jt} = \alpha_j + \beta_j C_t + \varepsilon_{jt}$. Different cost indicators were evaluated to determine which best characterized bidding behavior. In the case of sun and cottonseed oil, alternatives include the Fargo sunseed price, Gulf sun oil price, and the FOSFA index, each of which were rejected in favor of Rotterdam sun oil. For palm, Malaysian palm oil was chosen as the best cost indicator. and EU prices (crude palm CIF Northwest Europe). Different weighting schemes failed to improve the results. Tests were also conducted to allow for potential nonlinear relations in the bid functions. Neither polynomial (x^2) or double log forms provided a better fit than the linear form (i.e. lower R^2). A semi-log form, $B_{jt} = \alpha_j + \beta_j \log(C_t) + \varepsilon$, had a comparable fit. However in the relevant data range the log function is almost linear, so we simply used the linear form.

Regression Results

Results are shown in Table 5 and illustrated in Figure 11 for several suppliers.[9] 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 (MSE) shows the average deviation of bids from the regression line and provides a measure of predictive accuracy. The results indicate that J_s and O_s are more predicable competitors, while P_s and E_s are less predictable.

The probability of bidding, $p_{j,}$ is the fraction of tenders for which the firm submitted offers. G_s and F_s submitted offers in 92 and 96 percent of the tenders. Other bidders had more sporadic participation. Specifically, N_s, C_s, J_s and B_s submitted offers in less than 50% of the tenders. Thus, the effect of sporadic or random bidders is an important component in determining optimum bids.

There appear to be three distinct groups of firms participating in these tenders. These are characterized by the values of the statistical coefficients in their bid functions. Firms C_s, J_s, E_s and O_s have a high intercept, and a relatively large slope coefficient. In comparison, N_s, G_s and D_s have small intercepts and slopes. Firms in the third group have very large intercepts, and

Table 5. Bid Functions by Firm: Sun Oil

Bidder	***# of bids***	***Bid Function***		***MSE***	***R^2***	***Probability of Bidding***
		Intercept	*Slope*			
pooled	397	6.57	0.99*	9.53	.89	1
C_s	17	91.08	1.21*	10.08	.90	.31
J_s	28	60.38*	1.12*	7.35	.96	.46
E_s	23	45.36	1.10*	10.61	.87	.73
O_s	38	20.49	1.04*	7.50	.96	.65
N_s	24	-3.55	1.01*	8.20	.86	.26
G_s	72	5.95	0.99*	8.47	.93	.92
D_s	37	12.90	0.97*	9.97	.88	.69
F_s	51	45.21	0.92*	8.37	.86	.96
B_s	25	53.50	0.89*	8.87	.81	.46
P_s	34	83.64	0.83*	12.82	.62	.65

*Indicates significance at the 90% level.

[9] Only 10 bidders had sufficient observations for individual estimation.

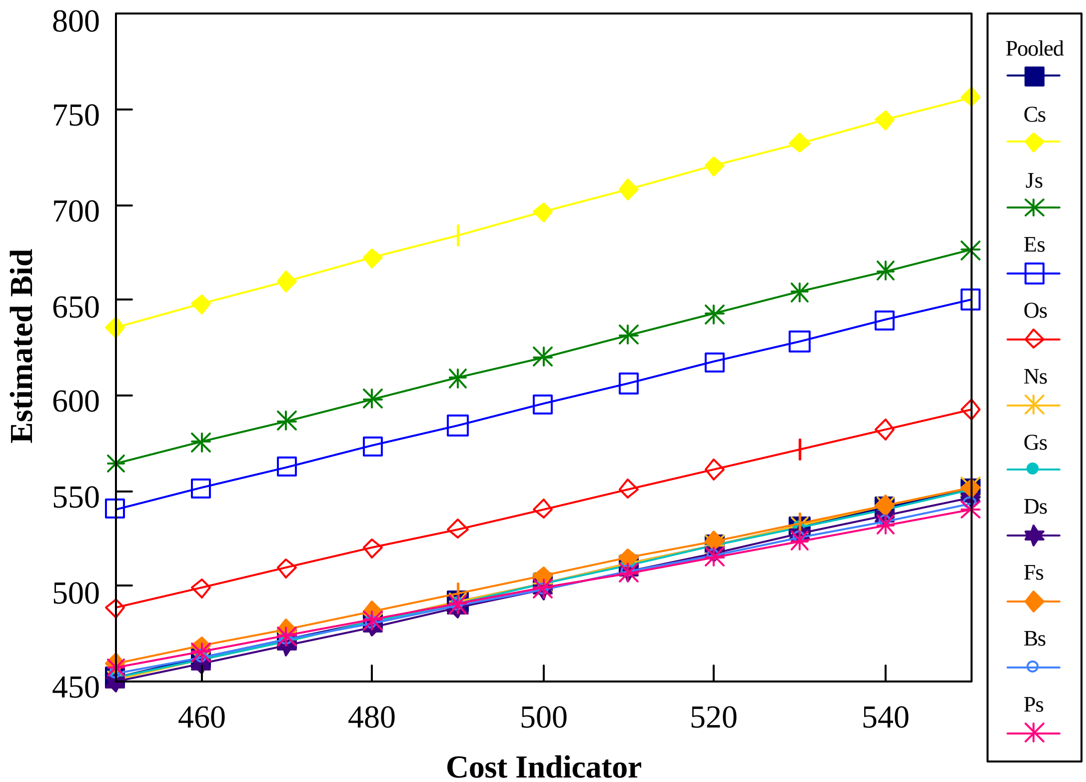

Figure 11. Estimated Bid Functions for Sun Oil

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 to determine if the bid functions were statistically different across rivals.[10] Test results for the 5 major bidders are shown in Table 6. The null hypothesis is rejected in 6 of the 10 pairings. This confirms that bidders are characterized by different bid functions. Strategically, bidding strategies of firms are clearly different.

[10] To test equivalence, the EES of the restricted and unrestricted models are compared. The F-value is given by (ESS_R - ESS_{UR})/2 over 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. For example, from D_s 's regression the ESS is 3482. From F_s 's regression the ESS is 3433. The sum of these is ESS_{UR} = 6915. Pooling observations and regressing gives ESS_R = 8370. The F-value is 9.05, which exceeds the table $F_{0.05}$ (2, 86), thus failing to accept the null hypothesis that the coefficients of two suppliers are equal. These results indicate we should treat each supplier separately.

Table 6. Results of F-test of Equivalent Regression Coefficients

Supplier	D_s	F_s	G_s	O_s
F_s	Reject**			
G_s	Accept	Reject**		
O_s	Accept	Reject**	Accept	
P_s	Reject*	Accept	Reject*	Reject**

* 90% confidence level
** 95% confidence level

Bid functions for the cottonseed oil tenders are shown in Table 7 and Figure 12. Compared to the sun oil bid functions, cottonseed oil tenders have 1) generally lower values for R^2; 2) higher MSEs, and 3) more sporadic participation in tenders by individual firms. Taken together these would suggest there is greater uncertainty for participants in cottonseed oil tenders, which ultimately is reflected in the bidding model.

Table 7. Bid Functions by Firm: Cottonseed Oil

Bidder	***# of bids***	***Bid Function***		***MSE***	R^2	***Probability of Bidding***
		γ	β			
pooled	145	-45.51*	1.12*	16.53	.74	
A_c	13	-256.16	1.64*	22.60	.64	.38
G_c	5	-84.37	1.23*	16.18	.77	.17
C_c	58	-79.98*	1.19*	9.73	.94	.83
F_c	8	15.30	0.99*	8.84	.63	.25
H_c	37	7.42	0.99*	12.97	.87	.54
J_c	6	129.68	0.75*	8.31	.74	.25

*Indicates significance at the 90% level.

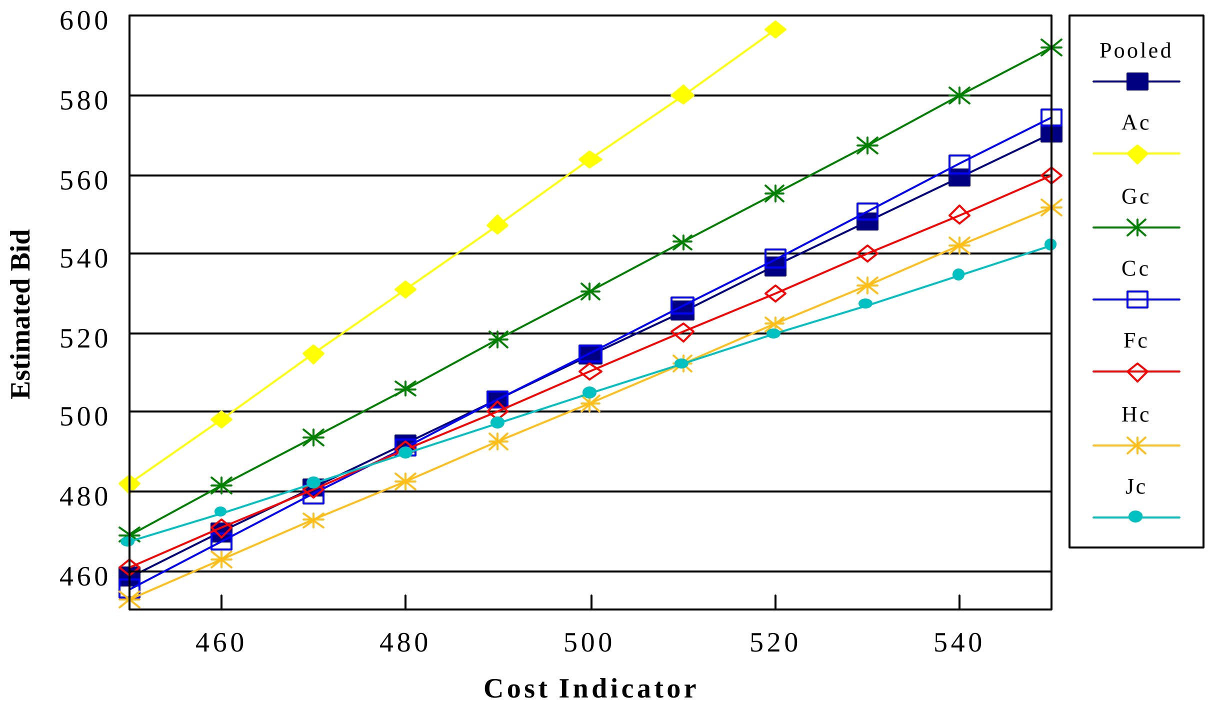

Figure 12. Estimated Bid Functions for Cottonseed Oil

Like the sun oil tenders, there appear to be distinct groups of firms in the cottonseed oil tenders, and two outliers. Firms G_c and C_c each have relatively low intercepts and large slopes. In contrast F_c and H_c have relatively large intercepts and smaller slopes. The two outliers are J_c and A_c; these firms' offers are less affected by changes in the value of the underlying commodity, and show a larger desired margin (higher intercept). Further, F_c and H_c are more competitive at lower values, and the others more competitive at higher values of the cost indicator

Results for the palm oil regressions are shown in Table 8. The results are more comparable to the cottonseed oil tenders than the sun oil tenders. With the exception of A_p, the probability of bidding in the tenders is greater than for the other oils, with G_p bidding in all tenders. An interesting feature of the palm oil results is that two bidders, E_p and D_p, have nearly identical bid functions. These firms behave nearly identically, suggesting a potential for effective signaling.

Table 8. Bid Functions by Firm: Palm Oil

Bidder	***# of bids***	***Bid Function***		***MSE***	***R^2***	***Probability of Bidding***
		γ	**β**			
pooled	50	-57.44*	1.38*	19.08	.85	1
A_p	6	-409.04	2.40*	11.20	.60	.29
E_p	9	-70.43*	1.42*	7.18	.98	.86
D_p	5	-71.17	1.41*	8.63	.98	.71
G_p	18	-8.73	1.22*	12.85	.90	1

*Indicates significance at the 90% level.

Bidding Strategies

In this section we develop optimal bids for a prototypical bidder k. First we show how to derive the probability of winning against an individual rival. Then we derive the optimal bid and expected payoff for bidder k competing against all rivals. Finally, sensitivity analysis is used to demonstrate effects of critical variables on optimal bids and expected payoffs.

Computing Competitors' Bid Distributions

Bid distributions were based on using estimated bid functions for specific competitors and used to derive probability distributions. Our prototypical bidder uses statistics (specifically, t values derived from bid function relationships) on past behavior of rivals to formulate bidding strategies. Statistics and representative parameters from firm D_S using the sun oil bid functions are shown in Table 9. For illustration we 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).

T-values were derived for different values of C using Equation 4. Different t values have probabilities associated with them, i.e., the probability of the specific opponent bidding at or below that offer level. Derivation of these probabilities are shown in the first two columns of Table 10.

Table 9. Statistical Parameters used to derive Bid Distributions: Ds

Statistical Parameter	*Value*
Standard error of the regression (σ)	9.97
Degrees of freedom (n and n-2)	37, 35
Coefficient estimates $\begin{pmatrix}\alpha \\ \beta\end{pmatrix}$	12.899 .9685
Mean cost ($\overline{C}$)	470
Current C_t (C^*)	500
Derived opponents' expected bid (O^*)	497.17

Table 10. Derivation of Bid Distributions

Bids	*t*	*Bayes P(W)*	*E(π)*
485	-1.185	.88	-13.17
490	-0.699	.76	-7.55
495	-0.211	.58	-2.92
500	0.276	.39	0
505	0.763	.23	1.13
510	1.250	.11	1.10
515	1.737	.05	0.68

Probabilities in Table 10 assume only one competitor represented by D_s's bid function and $C_k = C_t$ = \$500/mt. The results are the probability that bidder k will win and the expected payoff associated with different bids. The probability of underbidding, and therefore winning, is shown. Specifically, the probability of bidder k underbidding competitor D_s (i.e., winning the tender) with a bid of 485 would be .88. The probability of winning diminishes sharply for values greater than 505. Bid distributions for different competitors in the sun oil tenders are shown in Figure 13.

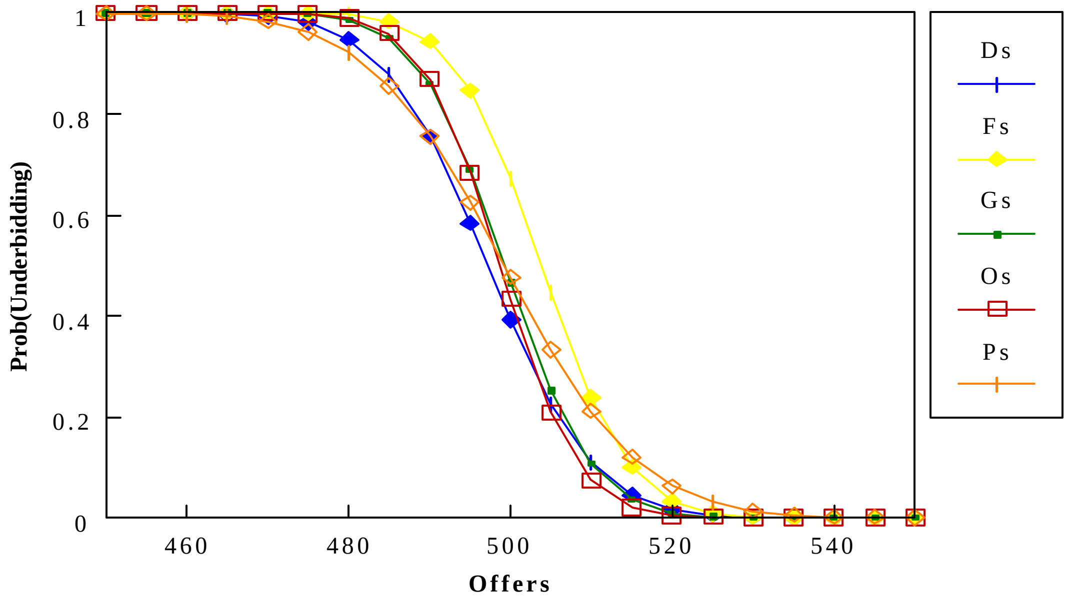

Figure 13. Sun Oil Tenders: Bidding Distributions for Major Bidders

Selected observations against individual bidders in the sun oil tenders are shown in Table 11 to allow a comparison of different bids and probabilities for different bidders. The values shown are the bids needed to underbid opponents with different probability levels (i.e., prob = .25, .5 and .75) and were derived from the regression parameters and the Bayes transformation. Values in the cells are the bids necessary to underbid the specific rival. For example, 510 is the bid needed to underbid F_s to win with prob = .25, if F_s were the only competitor. Hence, bidding against only F_s with a bid of \$510/mt would result in winning 25% of time. From this table, F_s is likely to bid highest, and P_s has the largest spread or most uncertainty.

Table 11. Bid Needed to Underbid Opponents with Specified Probabilities ($/mt)

Supplier	***Probability of Winning***		
	.25	.50	.75
	Optimal Bid to Win Versus Specified Opponents		
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

Factors Affecting the Optimal Bid

The optimal bid for bidder k (our prototypical firm) can be derived from the above distributions using the procedures described in Section 2. The expected payoff functions for specific bidders are shown in Figure 14. The expected payoff is highest when bidding against F_s, who tends to bid high. Bidding is profitable over a wide range of bids against P_s, which has the highest range of bids and the highest standard error in the bid function.

Several critical factors affect the optimal bid. In this section simulations are conducted to illustrate the effect of these variables on optimal bids.

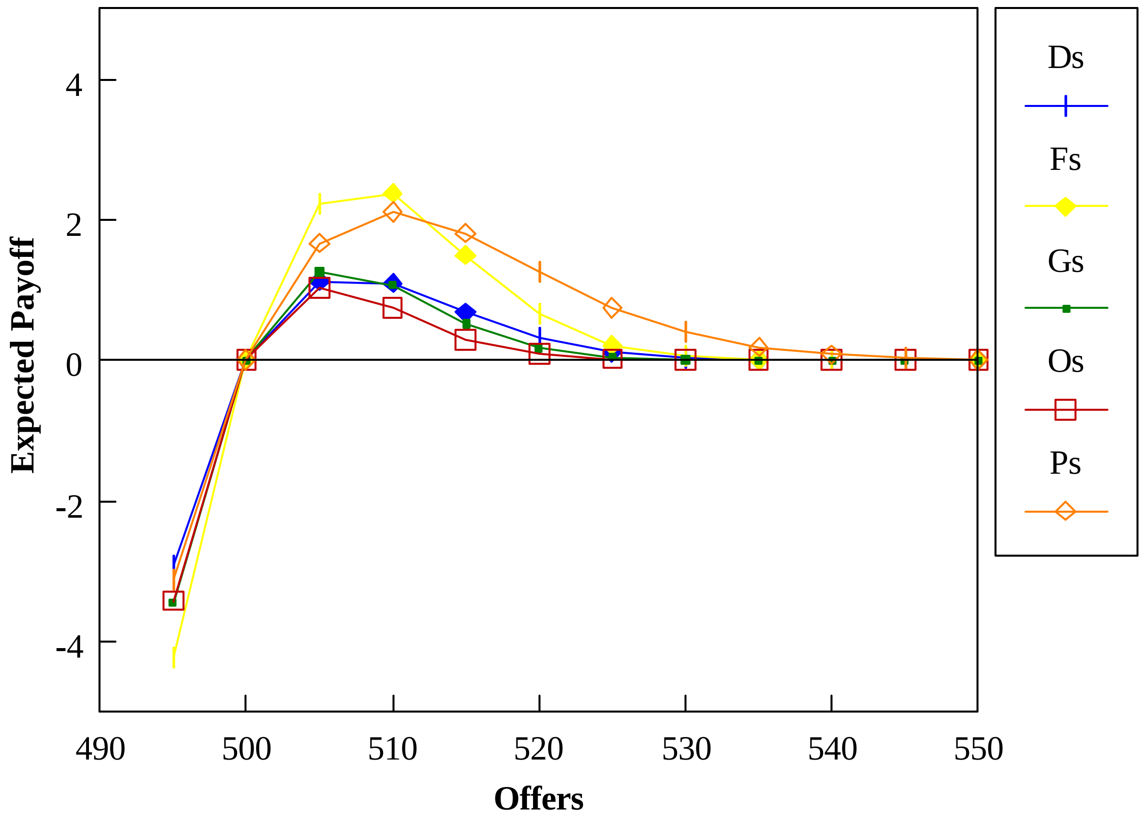

Figure 14. Sun Oil Tenders: Expected Payoff of Different Bids by Major Bidders

Number of Bidders The probability of underbidding more than one opponent is the joint probability of underbidding each opponent separately. Thus, with additional rivals there is a smaller probability of having the winning bid. Figure 15 shows the different bid distributions of the major bidders and the joint probability of underbidding up to all five bidders. To demonstrate these effects, bidders were added in order of likelihood of bidding, and the joint probability was computed for each set of bidders as shown. Even the addition of the last bidder lowers the

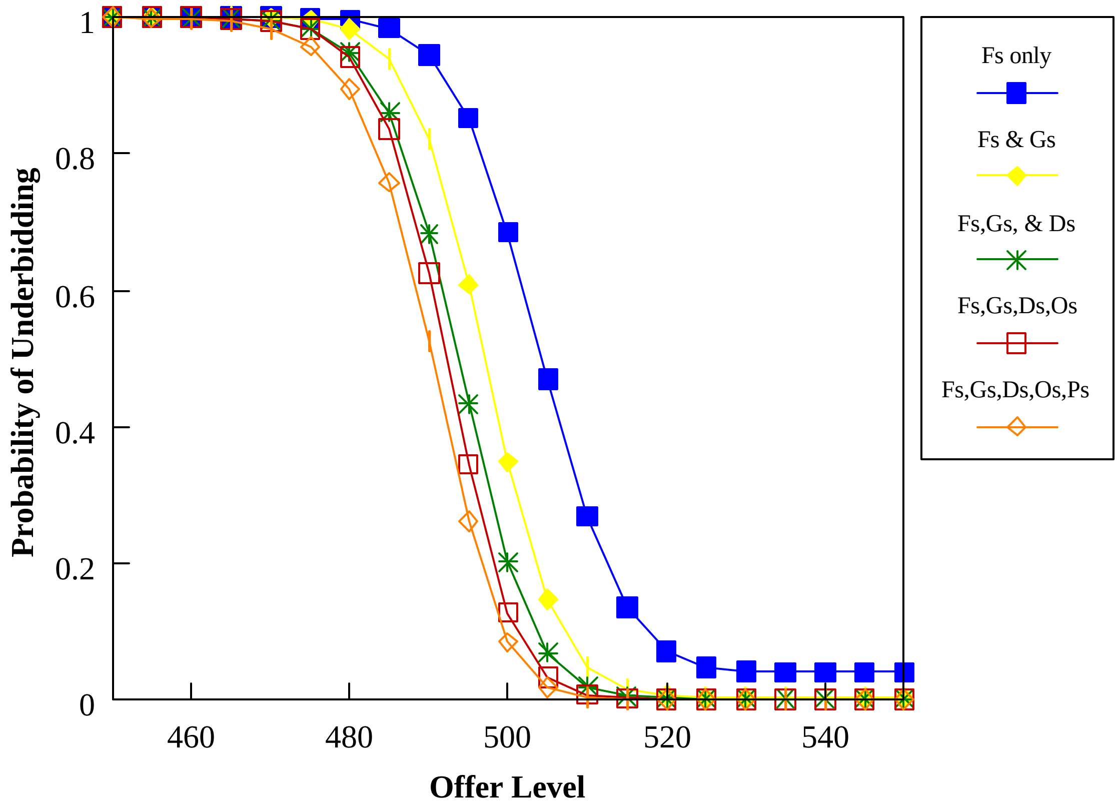

Figure 15. Impact of Number of Bidders on Probability of Underbidding

probability of underbidding by a noticeable amount. The expected payoffs associated with different numbers of bidders are shown in Figure 16 and summarized in Table 12. These were derived by successively incorporating the bid distribution of the bidder with the next greatest frequency of bidding.

Increasing the number of bidders from 1 to 5 (the average was 8 for sun oil) shifts the joint bid distribution [i.e., P(W)] leftwards. Figure 16 demonstrates the effect of an increase in the number of rivals on the expected payoff and optimal bid. Increases in the number of competitors reduces the optimal bid and expected payoffs. With only B_s bidding, the optimal bid was 508. Adding C_S as a rival lowers the optimal bid to 505. Expected payoff from the optimal bid also declines from about $2.74/mt to $0.73/mt.

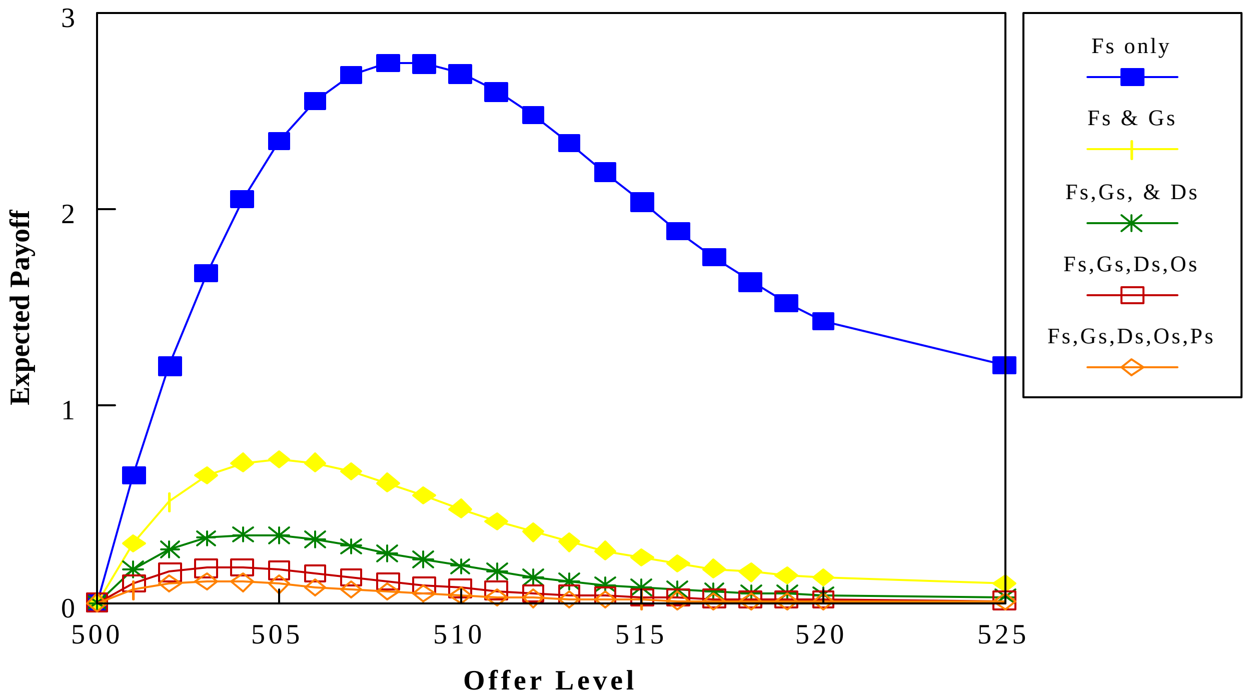

Figure 16. Impact of Number of Bidders on Optimal Bid

Table 12. Sun Oil Tenders: Effects of Number of Bidders

Number of Bidders: Firms Included	***Optimal Bid*** ($/mt)	***Expected Payoff (Eπ)*** ($/mt)
1: B_S	508	2.74
2: B_S,C_S	505	.73
3: B_S,C_S, A_S	504	.35
4: B_S,C_S,A_S,O_S	504	.18
5: B_S,C_S,A_S,O_S,P_S	503	.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. In this case, the added benefit diminishes as the number of bidders approaches five. In the case of sun oil with an average of eight bidders, there should be more than sufficient bidders to bid away excessive profits. However, for other oils, often the number of bidders is less than four, indicating that in some tenders competition may be less than adequate to bid away profits. This 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).

Random Bidders Bidders do not always bid in every tender. From a strategic perspective, the participation of some bidders must be viewed as random. In determining optimal bids, the probability of underbidding a specific opponent should be weighted by the probability that an opponent will submit a bid (as discussed in Monroe).

Bid distributions for sun oil without adjustments for the randomness in bidding are shown in Figure 17 and Figure 18 and includes the adjustment. Random participation in bidding essentially puts a lower bound on the probability of underbidding an opponent at the probability that the

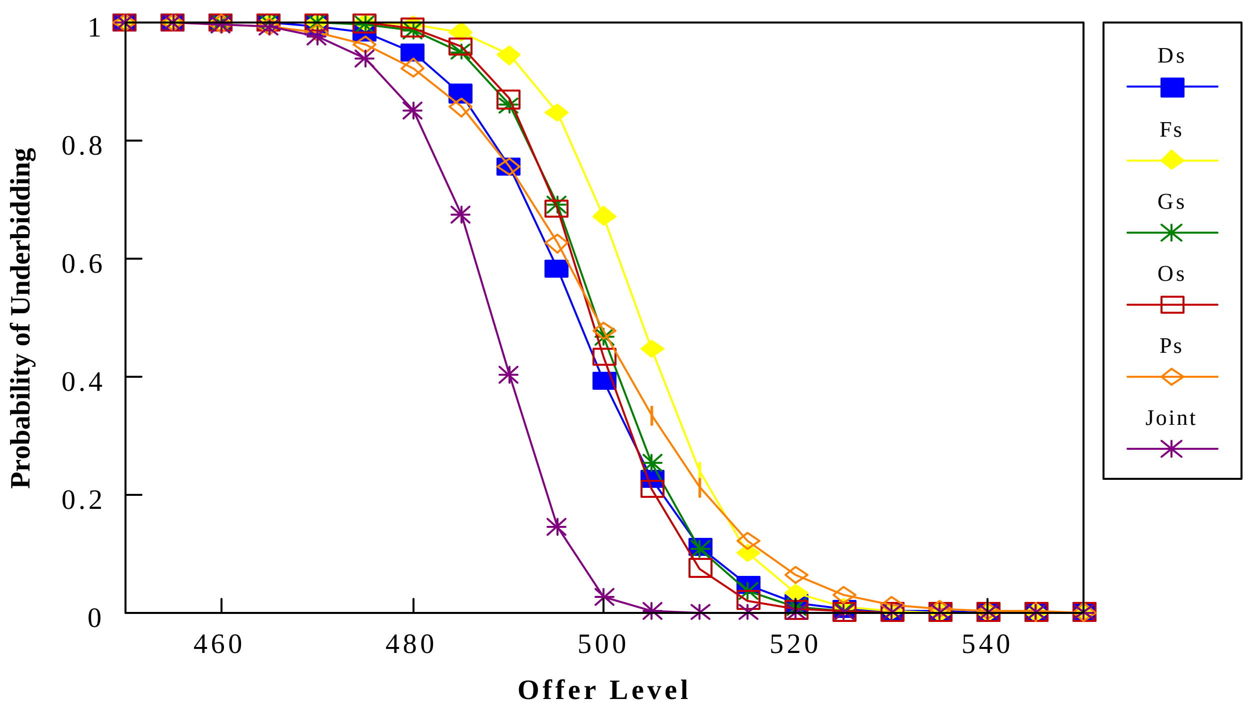

Figure 17. Probability of Underbidding When Suppliers Bid in Each Tender

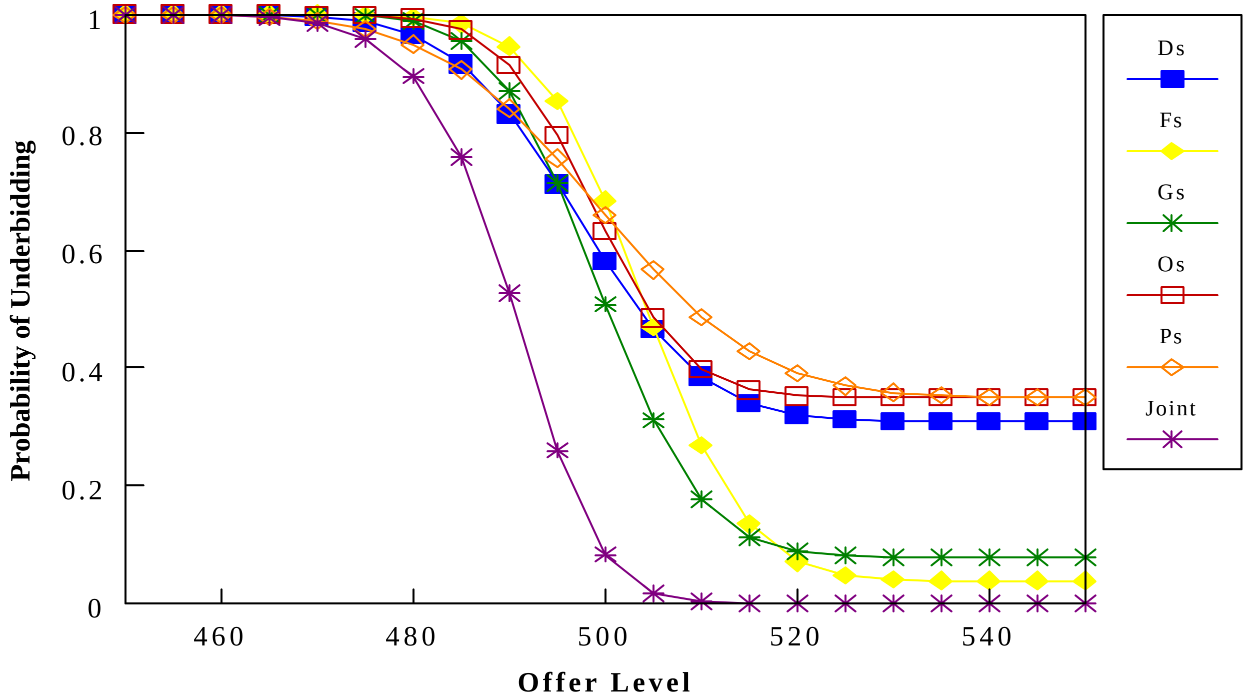

Figure 18. Probability of Underbidding After Adjusting for the Supplier's Probability of Submitting a Bid

opponent does not compete. For D_s, this is at 0.31, so almost a third of the time you would be underbidding D_s. The lower end of the joint probability shifts rightward for higher bids, but not by much. Before adjusting, a bid above 505 had no chance of winning; now a bid up to 510 has a slight chance of winning.

Effects of Information on Bid Strategies[11] Information about rivals' costs and bidding behavior has an important effect on bidding strategies. Indeed, one of the more interesting areas of competition relates to the role of information.[12] This is of interest both from a bidder perspective (i.e., in formulating strategies), as well as from an importer's (or auctioneer's) perspective (i.e., to the extent reveal information about bids to competitors, or reduce informational uncertainties).[13] Of particular importance is the extent that information about competitor's past bidding affects bidding strategies.

[11]See appendix for mathematical deriviation and proof of the effect of information on bidding strategies.

[12]See Phlips 1988; Dutta 1999; Rasmusen 1989; and Besanko 1996 for examples of recent literature on this topic. Caves (1977-78) and Wilson and Dahl provide discussions of the role of information in the international grain trade.

[13]Specifically, buyers may or may not release results of tenders, which bidders can use to refine estimates about rivals bidding strategies.

However, as illustrated below the effect of information is highly dependent on whether the firm is a high or low cost firm, as well as the number of competitors in the tender.[14]

To analyze these effects we treat MSE as the measure of information about bidders strategies (i.e., the predictability of bid distributions). We treat δ as 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 $\delta * MSE_i$, where $\delta = 2$, to represent a bidding competition with less information about all bidders. Optimal bids are then derived for two levels of information denoted by δ, 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: $C_k = 490$ and $C_k = 500$ and the cost identification for all other firms is C = $500/mt. Results are illustrated in Table 13 and Figures 19 and 20. Results demonstrate that increasing δ increases the optimal bids in all cases. For a low cost firm [with a higher P(W)], the P(W) decreases but not by enough to compensate for the effect of the increased bid. Thus, payoff decreases for a low cost firm in a bidding situation with less information. For a high cost firm [low P(W)] the opposite occurs. That is, the optimal bid increases, but the P(W) is such that the expected payoff increases. With N = 5 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 amongst rivals always raises (reduces) expected payoff for high (low) cost firms.

Table: 13. Impacts of Informational Uncertainties on Optimal Bids: Low and High Cost Firms

N (competitors)	***Cost (C_k)=490***				***Cost(C_k)=500***			
	Optimal Bid		$E(\pi)$		Optimal Bid		$E(\pi)$	
	δ=1	δ=2	δ=1	δ=2	δ=1	δ=2	δ=1	δ=2
2	498	502	3.61	3.24	505	509	.73	1.26
3	497	500	2.33	1.96	504	508	.35	.64
4	496	499	1.75	1.30	504	507	.18	.34
5	495	498	1.30	.89	503	506	.11	.21

[14] Dutta recently concluded that "every type of firm, and not just the more efficient ones, will find it in its best interest to reveal information about its costs." (Dutta, p. 338).

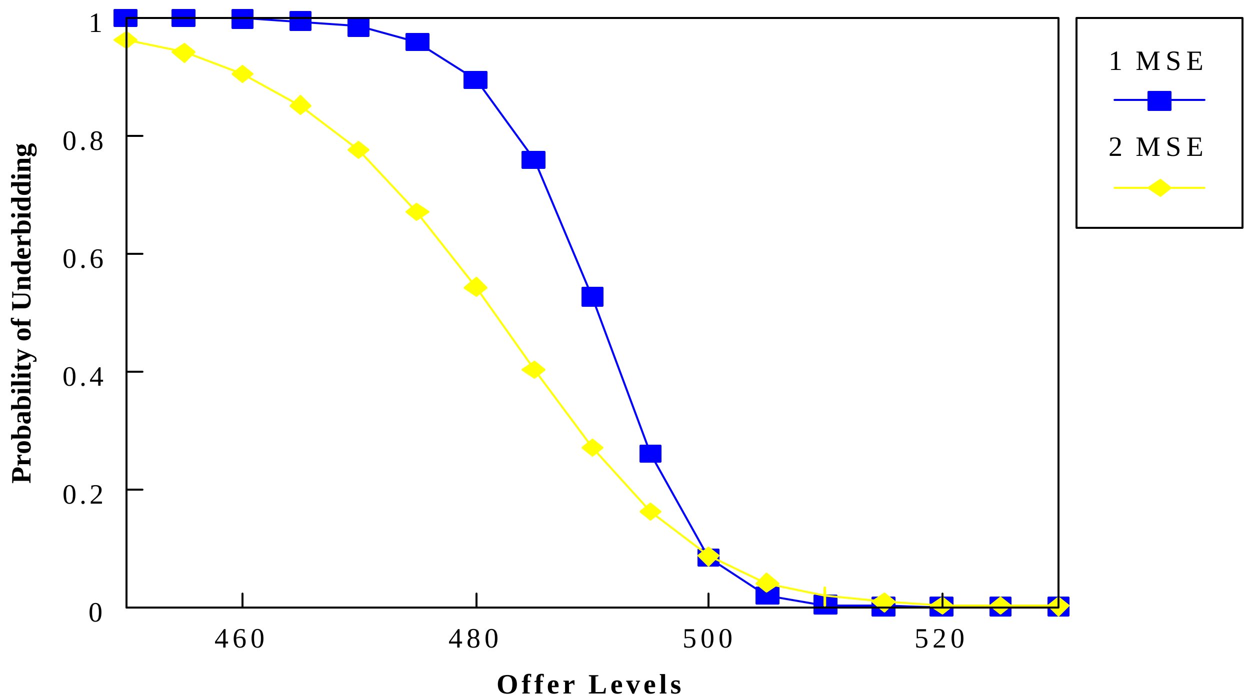

Figure 19. Impact of MSE on Probability of Underbidding

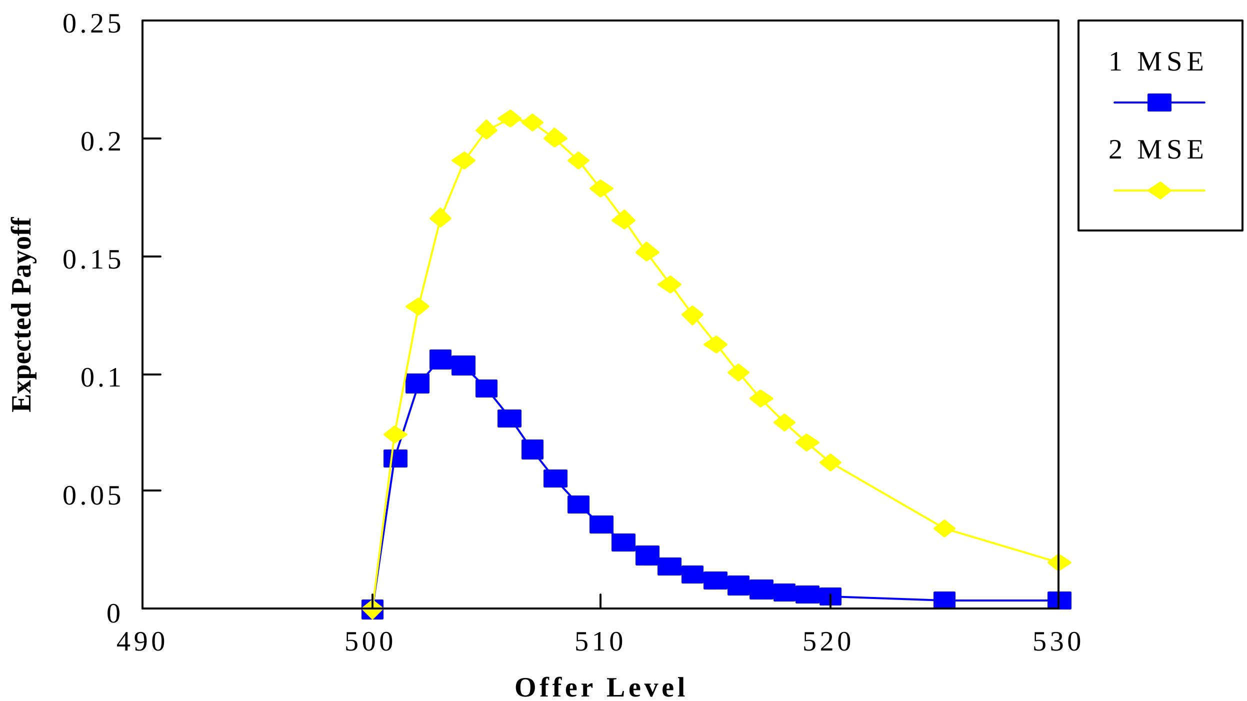

Figure 20. Impact of MSE on Expected Profit C_k = \$500

Figure 19 shows the effect of increasing the MSE of all major opponents on the joint bid distribution. Moving from δ = 1 to δ = 2 reduces the probability of underbidding opponents, i.e., for a given bid, the P(W) is greater if bidding against competitors that are more predictable (lower MSE). The effect of MSE on optimal bids and the expected payoff functions are shown in Figure 20. Increasing the MSE increases the expected payoff from the optimal bid. The expected payoff functions for C_k = \$490/mt are shown in Figure 21. In this case, the impact of an increased (decreased) standard error is to actually decrease (increased) the expected payoff from the optimal bid.[15]

These results have important implications for bidders and importers. Increases in the MSE for all competitors has 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 MSE (i.e., by releasing more information on bid results) to reduce 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.

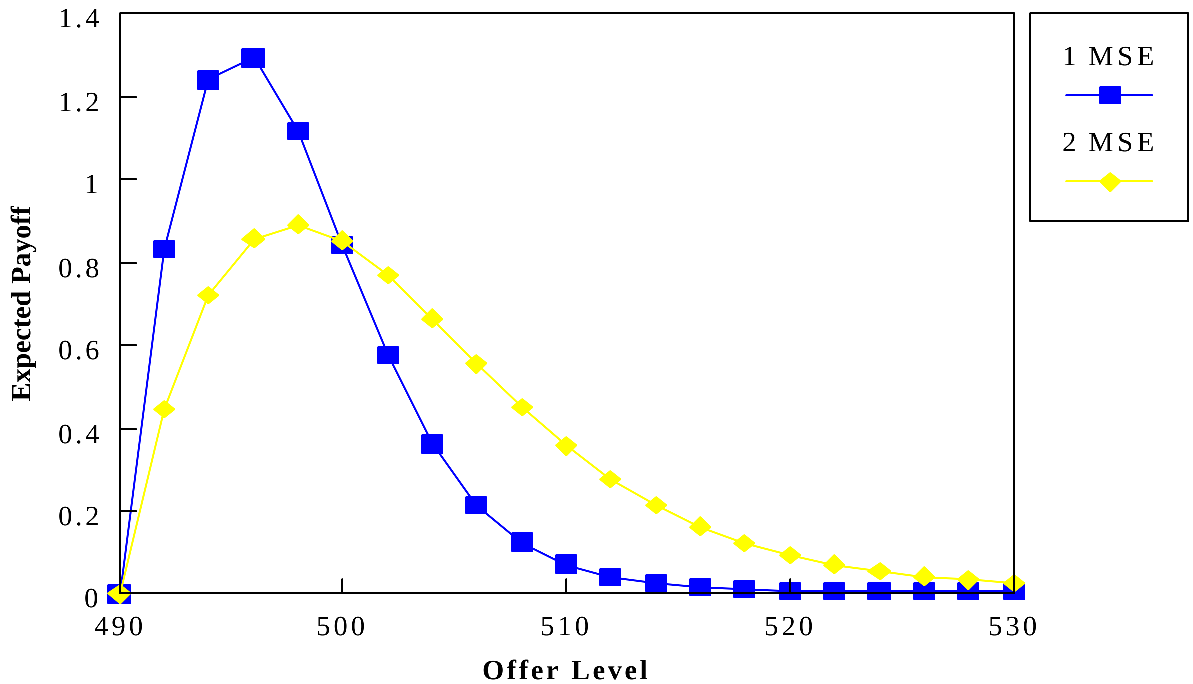

Figure 21. Impact of MSE on Expected Profit, C_k = \$490

[15]This was suggested in Rothkopf, and is proven in Appendix II.

These results have interesting comparisons across the different oils. The MSE reflects information that is revealed in the bidding process. For sun oil, these range from 7.5 to 12.8 and similarly for palm oil. However, the MSEs in the cottonseed oil bid functions were greater at 8.3 to 22.6. This greater information uncertainty has the effect of raising bids in cottonseed oil and yields a lesser advantage to low cost firms.

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 price determination as well as 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 payoffs to sellers. Though this analysis is applied to a particular set of detailed data, the approach and implications have many applications in other bidding situations in agricultural marketing and provide a contribution to understanding bidding strategies and competition.

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

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 to outside of historical ranges, the predictive density would be wider to account for that uncertainty in the sample.

Detailed data about the tendering for three vegetable oils (sun, cotton and palm) by Egypt were available for use in this study. Information included the values of bids submitted by each supplier in each tender over a period from 1990 to 1993. Several characteristics of these tenders are of interest. The number of bidders varied across tenders and across the different oils. In addition, the standard deviation varied across bidders. This suggests that auctions would play an important role in discovering the supplier with the lowest cost.

Bid functions were estimated for each supplier for each oil. Results indicated that generally, for all bidders the bids could be predicted with a relatively high degree of confidence using simple relationships and public data. However, there were several interesting characteristics from the results. For each oil tender there appeared to be groups of bidders characterized by differences in their bid functions. Of interest, in each there was one group characterized by high intercepts and lower slope coefficients; and another group with lower intercepts and larger slopes. These indicate that rivals have fundamentally different bidding strategies. Second, some bidders were highly predictable both with regards to their bidding behavior and their participation in each tender. In other cases firms were less predictable.

Taken together, these statistical characteristics have important effects on formulation of bidding strategies, on determination of optimal bids and on expected payoffs for the bidders. The bidding model was used to examine the effects of these and other variables on the auction results. Results indicated:

- The number of rivals is very important. An increase in the number of rivals has the effect of decreasing optimal bids, and lowering import prices for buyers.

- The frequency of random bidders in tenders has an important impact of results. There were several bidders who participated sporadically resulting in uncertainty in the number of bidders. 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. However, the effect depends on whether the firm is high or low cost. Results indicated that, in all cases, less information about rivals behavior has the effect of raising bids. However, the effect of information differs across firms. Greater uncertainty about bidder behavior reduces expected payoffs for low cost firms; but raises it for high cost firms.

Several important and interesting comparisons can be made across the different oils. The optimal bid depends on the number of bidders, the frequency of bidding by each, and the randomness of rivals both with respect to their participation in tenders and their behavior in previous tenders. Tenders for the vegetable oils differed in several important effects including the number of bidders, frequency of bidding, and predictability about bidder behavior. As a result, optimal bids and distribution of payoffs would vary across oils.

There are several important implications for participants in auctions. Buyers can 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. They can be 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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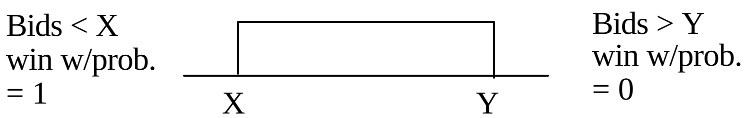
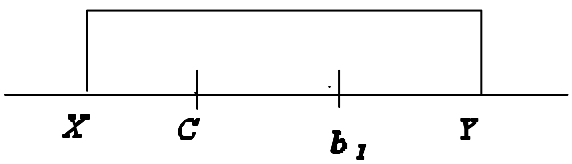
Appendix: Impacts of Information on Bidding Strategy

Changes in the knowledge of an opponents' bid distribution influences both the behavior of other bidders and the eventual outcomes of tenders. Comparative statics are derived below to show how a bidder adjusts his/her bid, given changes in an opponents' bid distribution.

Rothkopf has shown the profit-maximizing bid for a bidder, in a tender to buy a good, against an opponent with a uniform bid distribution. The bidding situation is reversed to demonstrate the selling situation. Begin with bidder 1, who has a cost of C and chooses a bid, b_1, for an upcoming tender. Bidder 1 has only one opposing bidder with a uniform bid distribution from X to Y as shown below.



Given X, Y, and C, bidder 1 chooses b_1, to maximize expected profit.



$$E(\pi) = \underbrace{(b_1 - C)}_{\substack{\textit{payoff}\\ \textit{of}\\ \textit{winning}\\ \textit{bid}}} \underbrace{\frac{(Y - b_1)}{(Y - X)}}_{\substack{\textit{probability}\\ \textit{of}\\ \textit{winning}}} \tag{1}$$

Equation (1) shows the payoff associated with b_1 and the probability of underbidding the opponent.

The bid that maximizes expected profits is the derivative of Equation (1) with respect to b_1:

$$\frac{d\,E(\pi)}{db_1} = \frac{d}{db_1}\,\frac{b_1 Y - b_1^2 - CY + Cb_1}{Y - X}$$

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

For this to hold, the numerator in the FOC must equal 0. Solving for b_1 gives:

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

which is simply the midpoint of own cost and highest opponent bid.

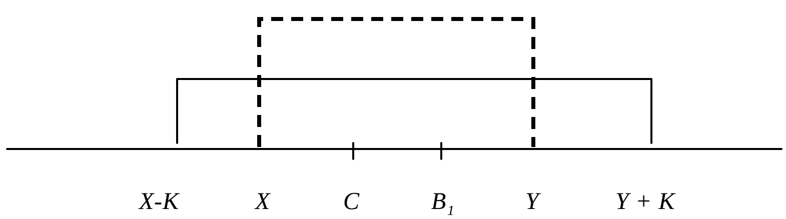
Substituting Equation (2) into (1) yields maximum expected profit.

$$E(\pi*) = \frac{\left(\frac{Y + C}{2} - C\right)\left(Y - \frac{Y + C}{2}\right)}{(Y - X)}$$

which can be reduced to

$$E(\pi^*) = \frac{(Y - C)^2}{4(Y - X)} \tag{3}$$

Imperfect information introduces greater uncertainty about the opponent's bids. An increase in the variance, by adding K to the tails of the distribution, can be represented as:



The payoff is unchanged at b_1 - C, but the probability of winning changes resulting in

$$\begin{aligned} E(\tilde{\pi}) &= (b_1 - C)\frac{(Y + K - b_1)}{(Y + K - X + K)} \\ &= (b_1 - C)\frac{(Y + K - b_1)}{(Y + 2K - X)} \end{aligned} \tag{4}$$

The new profit-maximizing bid is then obtained by solving

$$\frac{dE(\tilde{\pi})}{db_1} = \frac{d}{db_1}\frac{(b_1 - C)(Y + K - b_1)}{(Y + 2K - X)}$$

$$= \frac{Y + K - 2b_1 + C}{Y + 2K - X} = 0 \qquad \text{(F.O.C.)}$$

Solving for b_1 gives:

$$b_1^* = \frac{C + Y + K}{2} \tag{5}$$

This result indicates that if the variance of the opponents' bids increases, the optimal response is to increase the bid. As a buyer a small variance encourages lower bids.

Substituting (5) into (4) yields the new maximum expected profit:

$$E(\tilde{\pi}^*) = \frac{\left(\frac{C + Y + K}{2} - C\right)\left(Y + K - \frac{C + Y + K}{2}\right)}{(Y + 2K - X)} \tag{6}$$

which can be reduced to = $\dfrac{(Y + K - C)^2}{4(Y + 2K - X)}$

The extent that bidder l's expected profit changes with a change in the variance can be answered from two directions, using comparative statics. Both give insight into bidding strategy/behavior.

First, find the effect of K on $E(\tilde{\pi}^*)$

$$\frac{\partial E(\tilde{\pi}^*)}{\partial K} = \frac{\partial}{2K}\frac{(Y + K - C)^2}{4(Y + 2K - X)} \tag{7}$$

$$= \frac{(Y + 2K - X)(Y + K - C) - (Y + K - C)^2}{2(Y + 2K - X)^2}$$

The sign of (7) depends on the size of (Y + 2K - X) relative to (Y + K - C).

If $Y + 2K - X > (\leq) Y + K - C$, then

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

This simplifies to

$$\frac{\partial E(\tilde{\pi}^*)}{\partial K} \begin{cases} = 0 & \text{if} \quad C = X - K \\ > 0 & \quad\quad C > X - K \\ < 0 & \quad\quad C < X - K \end{cases} \tag{8}$$

This result indicates that increasing the variance raises (lowers) the expected profit from the optimal bid if bidder 1's cost is above (below) the opponent's new minimum expected bid. In general, if bidders submit profit-maximizing bids, then the expected profit of those bids increases if their cost is above the lowest bid submitted. For bidders with cost above the lowest bid submitted, they would see a decrease in expected profit from increased variance of opponents' bid distributions. Buyers could anticipate the relative changes in bidder behavior if they learned of changes in the bid distributions of low- and high-cost bidders.

Similarly, taking the derivative of the profit equation in (4) results in:

$$\frac{\partial E(\tilde{\pi})}{\partial K} = \frac{\partial}{\partial K} \frac{(b_1 - C)(Y + K - b_1)}{Y + 2K - X)} \tag{9}$$

which can be reduced to $\dfrac{(b_1 - C)(2b_1 - X - Y)}{(Y + 2K - X)^2}$

Note that $b_1 - C > 0$ for all bids above cost and $(Y + 2K - X)^2$ is always > 0.

The sign of $\dfrac{\partial E(\tilde{\pi})}{\partial K}$ depends on bidder l's bid relative to the opponents' bids.

$$\frac{\partial E(\tilde{\pi})}{\partial K} \begin{cases} = 0 & \text{if} \quad b_1 = \dfrac{X + Y}{2} \\ > 0 & \quad b_1 > \dfrac{X + Y}{2} \\ < 0 & \quad b_1 < \dfrac{X + Y}{2} \end{cases} \tag{10}$$

These results indicate that 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 (low) bids (bids above the opponent's mean), then expected profit from those bids would increase (decrease). This result is general and does not depend on cost assumptions or bidder behavior. The implications for the bidders that submit a range of bids could, therefore, be mixed -- either raising or lowering expected profits.