AAE Staff Paper No. 02001 January 2002

PARTICIPATION AND LEARNING IN AUCTIONS: BIDDING DECISIONS IN EGYPTIAN OILSEED AUCTIONS

William W. Wilson
Wesley W. Wilson

Department of Agribusiness and Applied Economics
Agricultural Experiment Station
North Dakota State University
Fargo, ND 58105

ABSTRACT

Auctions are common mechanisms for identifying prices and suppliers of commodities and are particularly important in agricultural marketing. Information asymmetries among bidders may be ameliorated over time through some form of learning. In this study, we incorporate prior decisions to participate, information from previous auctions, and firm-specific attributes to explain both the decision to bid and the level of the bid. Our analysis uses data from Egyptian oilseed tenders, an important market both for oilseeds and tendering. Because of the unbalanced nature of the panel data, we are able to evaluate the effects of signals received from previous tenders. We find that firms learn from previous auctions and can gain an informational advantage through some form of representation (e.g., by having an agent and/or direct sales agent to the country). Our results provide strong evidence that learning-by-doing affects the decision to participate and that learning affects the bid value. We also find that firms use outcomes of previous auctions to update information in both their decisions to participate in a market as well as determining the bid level. Finally, we find that firms with representation have a higher probability of participating in auctions and some evidence that they submit higher bids (earning higher returns).

Key Words: auction, bidding, tenders, optimal bids, learning

Acknowledgments

The authors gratefully acknowledge Bruce Dahl for his research assistance on earlier versions of this analysis. Comments on an earlier version were obtained from Bruce Dahl, William Ngange, Camilo Sarmiento, as well as by participants at seminars on this topic at North Dakota State University and the Universities of Western Australia, Manitoba, and Saskatchewan. Errors and omissions are the responsibility of the authors. This research was conducted under a National Research Initiative project titled *Strategic Effects of Transparency in International Wheat Markets* (NRI Project Number 97-35400-4436).

Single copies of this publication free of charge. Address your inquiry to: Carol Jensen, Department of Agribusiness and Applied Economics, North Dakota State University, P.O. Box 5636, Fargo, ND 58105-5636, (Ph. 701-231-7441, Fax (701-231-7400), (e-mail: cjensen@ndsuext.nodak.edu) or electronically at http://agecon.lib.umn.edu/.

TABLE OF CONTENTS

PAGE

LIST OF TABLES

LIST OF FIGURES

PARTICIPATION AND LEARNING IN AUCTIONS: BIDDING DECISIONS IN EGYPTIAN OILSEED AUCTIONS

William W. Wilson and Wesley W. Wilson*

INTRODUCTION

Auctions and bidding play an important role in agricultural marketing. A popular and noteworthy use of auctions (or what is now commonly referred to as reverse auctions) is that of import tendering which is used for both price determination and allocation of purchases among sellers. In fact, an important form of inter-firm and inter-country rivalry involves bidding strategies. Specifically, buyers use auctions extensively in the procurement of agricultural products to identify the low-cost supplier and to promote competition among rivals. Given that costs vary randomly through time, across competitors, and cannot be directly observed by buyers, auctions are an efficient way to identify the low-cost suppliers. For these reasons, auctions have traditionally been and continue to be an important mechanism affecting competition in this industry.[1]

Information is a crucial element in determining bids among competitors in bidding games. Firms with more refined information enjoy a competitive advantage. Though the structure of the world grain and oilseeds industries have been the subject of numerous studies, there has been limited attention to bidding strategies which is an integral element of firm conduct. Some of that literature has focused on the role of information which is touted as an important element in understanding the sources of economies and competitive advantage among

---

*Authors are professors in the Department of Agribusiness and Applied Economics, NDSU, Fargo, and the Department of Economics, University of Oregon, Eugene, respectively.

[1]In the case of grains there are numerous examples of auctions playing an integral role in marketing. These include not only import tendering as described in this study, but also auctions for EEP allocations, for rail rates and service (Wilson, Priewe, and Dahl), and import tendering for barley in Japan (Rampton). Auctions were also proposed and adopted as an alternative in Canadian grain marketing (Estey and Kroeger).

grain and oilseed firms. Caves identified information as a crucial source of competitive advantage in commodity-based businesses. Cook suggested that the exporting industry would likely evolve to include two strategic groups, one being physical asset intensive the other more informational intensive. This has in fact been evolving. During much of the period from the 1970s through the 1980s, grain trading firms sought to develop competitive advantage based on their information networks. Information has important characteristics which influence conduct. Most important is that it involves a high fixed cost, thus yielding substantial economies, and that it is perishable. Some grain trading firms have pursued strategies to build extensive overseas networks through direct representation, agents, or vertical integration. In each case, information procurement is an important element motivating these strategies. However, how information affects conduct and, in this case bidding strategies, are not well understood.

There is an extensive literature on auctions and bidding. Cassady provides a historical overview of auction strategies and mechanisms. More recently, several bibliographies (McAffee and McMillan (1987, 1996b); Engelbrecht-Wiggans; Milgrom (1985, 1987 and 1989) and Rothkopf and Harstad) review the literature on auctions and bidding strategies. Recent texts (including Monroe, Nagle and Holden; and Lilien and Kotler (1992); Rasmusen; Kottas and Khumawata and Sewall) provide some practical motivations for auctions and analytical approaches to bidding strategies. There have been several recent studies on empirical auctions. Examples include Brown, Hausch and Li; Crampton (1995); Hendricks and Porter; Hendricks, Porter and Wilson; Hughart; McMillan (1997); McAfee and McMillan (1986, 1996a, 1996b); Oren and Rothkopf; Reece; and Wilson (1988 and 1992). Recent examples in agriculture include Bourgeon and LeRoux (1996a, 1996b and 2001) for EU export tenders and Latacz-

Lohmamm and Hamsvoort for the Conservation Reserve Program, and Hayes et al. and to determine demands for new goods (Shogren, List, and Hayes).

Several studies have analyzed some specific issues identified as important in this study using results from experimental auctions. Battalio et al. (1990) analyzed the impact of the number of bidders on strategies in first price sealed bid auctions. Dyer et al. (1989) examined how bidders respond to uncertainties about competitor bids. McAfee and McMillan (1987) illustrate that bids are impacted by the number of bidders, and that better informed bidders earn greater returns in common value auctions. Finally, attention has been given to the winner's curse (e.g., Coy and Thaler) and appropriate strategies to avoid its impact (R. Wilson 1987).

Lesser attention has focused on factors affecting bidding strategies in real auctions. A notable exception is Porter and Zona who studied bidding strategies in milk procurement. In a reverse auction, sellers have two fundamental and potentially related decisions. These include whether to bid, and if so, how much to bid. Taken together, we refer to these as components of a bidding strategy. These are potentially impacted by numerous influences among which include expected costs and perceptions of the intensity of competition. In addition to these, the role and impact of "learning" or experience, as well as other idiosyncratic firm characteristics impact bidding strategies. Learning can occur through participation in past auctions as well as through information on the results of the preceding auction. These provide potential informational and cost advantages for some, but not all firms, and result in important asymmetries among firms.

The purpose of this study is to assess how these factors impact bidding strategies. The results are particularly useful in understanding sellers' strategies regarding participation in bidding as well as determination of bid levels. Detailed data were from sunoil tenders by an Egyptian import agency. The results indicate that participation decisions are independent of bid level decisions, that there are unobserved and asymmetric firm effects which impact participation decisions, and that learning and information from previous auctions have important impacts on bidding strategies. The next section describes our empirical models of bidding strategies. The following section presents the statistical analysis of bidding strategies. The final section provides a summary, some conclusions, and implications.

ANALYTICAL MODELS OF BIDDING STRATEGIES

Our analysis focuses on two key decisions. Suppliers maximize expected profits by choosing to participate in an auction, and, if they do, the bid level. We first describe the optimal bid and then the choice of whether the firm participates or not.

Given the firm participates, we assume they choose to maximize the expected payoff $E(\pi)$ which is

$$E(\pi) = (B - C - k)\ prob(B < \bar{b}) - k[1 - prob(B < \bar{b})] \tag{1}$$

where B is the bid, $\bar{b}$ is the lowest bid amongst rival bidders, C is marginal cost, k is the sunk cost of bidding and participation in the market (with or without representation) and $prob(B<\bar{b})$ is the probability of winning which we will denote below as $P'(W)$.

To win, a bidder must dominate all other bidders. The probability of underbidding each specific opponent across a range of potential bids is the joint probability of underbidding all opponents. With N independent bidders, the probability firm i wins is:

$$P_i(W) = P_{i,1}(W) \cdot P_{i,2}(W) \cdot,\ldots, \cdot P_{i,N}(W) = \prod_{j=1}^{N} P_{ij}(W) \tag{2}$$

where $P_i(W)$ is the joint probability of underbidding all opponents, and $P_{ij}(W)$ is the probability of a bidder i winning against competitor j.

Firms do not participate in every tender. We follow Simon and Nagle and Holden and treat the number of bidders as uncertain. The probability of winning against a random bidder is $P'_i\,(W) = p_{jc}P_i(W) + (1\text{-}p_{jc})$ where p_{jc} is the probability that competitor j bids, $P_i(W)$ is the probability of winning, and ($1\text{-}p_{jc}$) is the probability that competitor j does not bid.

The optimal bid, which maximizes expected profits is defined as

$$\underset{B}{Max}\ E(\pi_i) = (B - C)\ P'\,(W) \tag{3}$$

The optimal bid (B*) is the bid that solves the associated first-order condition given by:

$$\frac{\partial E(\pi)}{\partial B} = P'\,(W) + \frac{\partial P'(W)}{\partial B}\ (B^* - C) = 0. \tag{4}$$

Solving 4 for the optimal bid yields

$$B^* = C - P'\,(W)\ \frac{1}{\partial P'(W)/\partial B} \tag{5}$$

There is a fundamental tradeoff in determining the optimal bid. Higher bids result in a greater payoff, but, a lower probability of winning. The product of these two functions yields $E(\pi)$, the maximum of which is the optimal bid. Deviations from this affect both the probability of winning and the payoff, and would result in a lower $E(\pi)$. The optimal bid ($B*$) is affected by costs and the relationship between the probability of winning and the bid. As the number of bidders increases (or the participation rate of bidders increases), $P_i\,(W)$ decreases resulting in lower expected payoffs from bidding and reduced bids ($B*$).

Theoretically, the sunk cost of bidding *(k)* does not have a direct impact on the optimal bid but may have an indirect effect. k represents sunk costs associated with participating in a market and bidding (i.e., cost of representation and bid preparation costs). It is possible the bidder is influenced by these sunk costs. Simon (p. 279) observes that the greater the value of k, the greater is the pressure to participate and psychological incentive to win by lowering bids.

Substitution of B^* into equation 1 yields the maximum expected payoff from bidding – the bidding payoff (π^B). However, it may not always be optimal to bid. That is, sales in an alternative market may be preferable. In this case, firms can participate in a spot market the value of which is interpreted as the opportunity cost of bidding in a tender. The payoffs from the alternative is π^A. A condition for participation in the tender is that expected payoffs from participation must be at least as large as the payoffs from the alternative, i.e., $E(\pi^B) \geq E(\pi^A)$. As prices in the spot market (the alternative market) increase, the likelihood of participation in the tender decreases.

EMPIRICAL APPLICATION

We specify two empirical models about firm bidding strategies which follow directly from above. We model whether or not a firm bids, the participation decision, and the value of bid submitted conditional on participating. We first describe our model of participation and then the bidding model conditioned on participation.

Tender Participation Decisions

The participation decision follows from the condition that to participate in the auction expected returns exceed returns from the outside alternative, i.e., $E(\pi^B) \geq E(\pi^{A.})$. We observe whether a bid is submitted, i.e., $\delta=1$, if $E(\pi^B) > E(\pi^A)$. We use the index function approach to modeling participation. The empirical model is:

$$\begin{aligned} P(\delta_{it} = 1) &= P(\pi_{it}^B \geq \pi_{it}^A) \\ &= P(\beta^T X_{it} \geq \varepsilon_{it}) \end{aligned} \tag{6}$$

where *P(.)* is a probability function, X_{it} is a vector of explanatory variables, and β is a set of unknown parameters.

Expected payoffs from participation depend on the bid value, the likelihood of winning, and costs of participation, while payoffs from non-participation depend on the price from an outside option (i.e., opportunity cost in the alternative market). Most of these variables are not directly observable and are, questionably, endogenous. To avoid these complications, we model the difference between expected payoffs from participation and non-participation as a reduced form and estimate the decision as a logit model.

As explanatory variables, we include the price of the outside option as well as a set of firm specific characteristics. We expect the price of the outside option (P^A) to have a negative effect on the probability of participation. We include variables representing firm specific characteristics to reflect effects of learning, representation, unobserved firm characteristics and participation in previous tenders.

"Learning by doing" is important in business strategy (Oster 1994) and has become subject of a growing literature both theoretically and empirically [(Lieberman 1984), (Gruber 1992), (Dick 1994), (Irwin and Klenow 1994), (Jarmin 1994), and (Brist and Wilson 1996)]. Generally, this literature holds that firms reduce costs through experience or learning-by-doing.

In particular, unit costs are allegedly impacted by cumulative output. Typically, cumulative output has an asymptotic impact on unit costs, with greater reductions in earlier periods, tapering off as experience increases. Each of these studies capture these effects through a learning-by-doing variable which is the firm's cumulative production over time. As firms learn through previous production decisions, costs fall. In our case, we use the cumulative sum of decisions to participate as a measure of the costs of information gathering and participating in the market. In both cases, we expect costs to fall with experience making participation decisions more likely.

The impact of learning by doing is that firms' unit costs decline through learning. These impacts are prospectively fairly important, particularly in commodity type industries. Lieberman showed that the learning curve effect may overshadow scale economies in petrochemicals. There are at least three sources of learning. First, economies of distribution decline as the cumulative number of trades increases (e.g., the prospect of combining shipments from multiple transactions results in lower shipping costs). Second, participaton in auctions require the formation of expected bids. The costs of gaining information to formulate bids and the sunk costs of participation likely fall with market experiences. These would be represented by $k>0$ in the theoretical model. Third, through experience firms likely gain knowledge of competitiveness of bids and the profitability of operating in the market.

We examine several measures of learning. Following directly from previous literature, we use a measure defined as the cumulative sum of participation decisions made by a particular firm. At time period t, a firm's experience would be the number of times through period t-1, in which the firm has participated in the market. To reflect diminishing returns, we define our

$$IL_{it} = 1/\left(1 + \sum_{s=0}^{t-1} \delta_{is}\right)$$

learning variable as an inverse measure. Increases in the cumulative sum of participation decreases our learning measure, and the likelihood of participation increases. We expect the sign on the coefficient to be negative. This measure has the advantage of introducing a non-linearity that allows the effectiveness of learning to dissipate.

We also examine the effects of learning with two other variables. Specifically, we use lagged values of participation as explanatory variables. Learning may depend not just on past participation (the sum of which is equivalent whether the sum is collected in the distant past or the near past), but also the period of time in which learning occurs. An alternative measure of learning is a distributed lag of past participation rates. Empirically, we use L1 and L2 which represent lagged values of participation in the previous one and two tenders, respectively. We expect the coefficients on each of these two variables to positively influence participation, and for the coefficients to become smaller with the length of a lag, i.e., the effect of being in the auction last period is greater than the effect of being in the auction two periods before.

We include two other explanatory variables. First, the 20 firms are largely multinational firms that supply or potentially supply the market. All supply is done through exportation and not through foreign direct investment. Seven of the firms have representation in Egypt. To reflect this greater commitment, we incorporate a dummy variable (R) taking a value of one if the firm has a representation office and a value of zero otherwise. Our conjecture is that if a firm has representation they are more likely to participate in the auction market. Indirectly, these are sunk costs related to participating in a market and would have an impact on the value of k. Though this does not directly impact the optimal bid price, it may have an indirect impact due to informational advantages.

Our data are repeated observations on tenders, and firms observe the outcome from previous tenders. Information gained from previous auctions has the potential to affect participation and bidding behavior. We include another set of variables that reflect results of previous auctions. We examine two measures including the price of the outside option divided by the average bid in the previous tender $(P^A_i / \overline{B})_{t-1}$, and the price of the outside option divided by the winning bid in the previous tender $(P^A_i / B^W)_{t-1}$. As a set of final explanatory variables, we included a set of firm-specific effects. These dummy variables are included to control for unobserved and systematic effects specific to a firm but unobserved in our data.

In the most general form, the specifications we examine are special cases of:

$$P(\delta_{it} = 1) = P(\beta_{it} + \beta_1 P_t^A + \beta_2 (P_i^A / \overline{B})_{t-1} + \beta_3 (Learning_{it}) + \beta_4 (Representation_i) + \varepsilon_{it} \tag{7}$$

where the price of the alternative and the bid in the previous time period can take on different measures as described above.

Bid Level Decisions

Our model of bidding behavior follows directly from the previous sections. The base model includes, the price of the outside option, information from the previous auction, and firm specific characteristics (representation, learning and firm dummy variables).[2] The estimated model is:

$$B_{it} = \gamma_0 + \gamma_1 P_t^A + \gamma_2 B_{t-1}^W + \gamma_3 (Learning_{it}) + \gamma_4 (Representation_i) + \varepsilon_{it} \tag{8}$$

[2]We examined the potential bias from sample selection and found no evidence that the decision to participate in a tender is correlated with the level of the bid (i.e., there is no significant sample selection bias).

We use the Rotterdam price as the price of the outside option. Rotterdam is a highly transparent and readily tradeable market and consequently is included as a measure of the outside alternative for the procurement agency. It is with this price that sellers must compete. We expect then that bids submitted must dominate the Rotterdam price, and as we discuss later, the Rotterdam price is highly correlated with bids. Discussions with market analysts along with this conjecture suggest that the Rotterdam price is the appropriate measure explaining bid. [3]

We also allow signals from previous tenders to enter the model. We ultimately used the winning bid in the previous tender, B^W_{t-1}. We experimented with alternative forms of updating such as the ratio of the bid submitted and the winning bid from the last tender in which the firm participated, the ratio of the outside option price and the winning bid from the last tender. The results reported dominate but do not differ qualitatively.

Learning and representation captures the same effects as discussed earlier. We explore two different functional forms -- a linear and a log form. In the linear specification, learning is measured as described above, the inverse measure of learning, while in the log specifications we measure learning as a direct measure i.e., $L_{it} = 1 + \sum_{s=0}^{t-1} \delta_{is}$. Finally, we also consider effects on bidding that are not observed by the inclusion of fixed effects (FE).

DATA DESCRIPTION

A data set was developed from bids received during tenders by the Egyptian procurement agency responsible for importing vegetables oils. Tenders were generally held monthly at about

[3]However, we also estimated the model with U.S. Gulf prices and the results, while numerically different, do not lead to different qualitative conclusions.

the same time each month and asked for bids for sunoil. The time period for the analysis presented here cover all tenders from January 1990 through August 1993. Suppliers are exporting firms, some being both the processor and exporter, others being processors' agents. Sometimes suppliers make multiple offers at different bids (i.e., scaled bids) which is a common practice in international tendering. We treated these as separate offers by that particular supplier.

For each tender, the agency identifies minimum and maximum quantities that will be purchased. Firms then choose whether to bid. In some tenders, the agency selects more than one winning bid. In short, the result is that there are unequal numbers of bidders across tenders, multiple bids submitted by individual firms, and, perhaps, multiple winning bids. We consider each in turn.

Over the three-year period 20 different firms submitted bids in 26 tenders. The number of firms submitting bids or suppliers, varied over time. For each tender, the number of bidders and the number of total bids varied because the number of bids each supplier submitted varied. The number of bids exceeds the number of bidders because of multiple bids. The number of firms participating ranged from 2 to 11 with an average of 7.7 firms per tender. If the firm chooses to bid, it submits one or more bids each consisting of a price and quantity to be delivered. Frequently firms submit multiple bids. The result of this process is that there are unequal numbers of bidders across tenders, multiple bids submitted by individual firms, and, perhaps, multiple winning bids.

Oilseed prices were taken from *Oilworld* Annual Reports and were concurrent with the date of the tender. Finally, firm representation was derived through interviews with major importers in this market.

EMPIRICAL RESULTS

The empirical specifications have variables with several measurements and estimation alternatives. First, we tested for selection bias in the bidding equations. In no case (specification) did we find significance i.e., the participation models and the bidding models can be estimated separately without bias. We then proceeded through each of the specification issues and report models with and without firm specific effects and with alternative measurements and functional forms. We first describe the participation decision results and then results of the bid level models.

Participation Decisions

The results are presented in Table 1 with several different models with and without controls for firm heterogeneity. We first estimate a model with an intercept and world price (model 1). We then introduce firm intercepts (model 2) and firm interactions (model 3). In the final model, we replace world price with tender dummies (model 4).[4] Heterogeneity across firms was controlled using firm specific dummy variables. Owing to the representation variable, there are two base dummies. Results are based on a reduced set of firm dummies. Results are based on a reduced set of firm dummies. Comparable results for the full set of firm dummies are

[4]The world price variable is constant across firms for each tender. Inclusion of both tender and world price results in a singular hessian matrix.

Table 1. Participation Decision Coefficient Estimates

Variable[a]	Model[b] 1	2	3	4	5	6
Constant	1.619	2.573**	2.402	1.911	4.844**	4.332*
	(1.273)	(1.467)	(1.369)	(1.525)	(1.740)	(1.960)
P^A	-.003	-0.005**	NA	NA	NA	NA
	(0.002)	(0.003)	NA	NA	NA	NA
$(P^A_i / \bar{B})_{t-1}$	NA	NA	-2.051**	-2.451**	NA	NA
	NA	NA	(1.164)	(1.302)	NA	NA
$(P^A_i / B^W)_{t-1}$	NA	NA	NA	NA	-4.141*	-4.629*
	NA	NA	NA	NA	(1.452)	(1.644)
$Repre_i$	1.006*	-0.234	1.031*	0.899*	1.075*	1.233*
	(0.204)	(0.334)	(0.215)	(0.317)	(0.230)	(0.314)
$Learn_{it}$	-1.983*	-0.396	-2.711*	-1.961*	-2.706*	-1.847*
	(0.311)	(0.411)	(0.387)	(0.427)	(0.425)	(0.463)
%Correct						
all	69	76	71	80	72	80
In=1	47	60	48	64	55	65
In=0	84	87	83	89	82	89
Chi-Square	94	219	117	211	104	198
Fixed Effects	No	Yes*	No	Yes*	No	Yes*
N[b]	520	520	500	500	440	440

[a] * and ** represent statistical significance at the 5 and 10 percent levels, respectively.
[b] Specifications 1 and 2 reflect all the data; Specifications 3 and 4 require the omission of the first tender, consisting of 20 firms, Specifications 5 and 6 require the omission of tenders 1, 4, 6, and 16 due to the fact that winning bids were not available for tenders 3, 5 and 15, and tender 1 did not have a preceding tender.

Table 1. (Continued)

Variable[a]	Model[b] 7	8	9	10	11	12
Constant	-0.442	0.585	-0.710	0.104	-0.599	0.135
	(1.922)	(2.001)	(2.090)	(2.167)	(2.139)	(2.221)
P^A	-0.004	-0.005	NA	NA	NA	NA
	(0.003)	(0.0036)	NA	NA	NA	NA
$(P^A_i / \bar{B})_{t-1}$	NA	NA	-1.566	-2.358	NA	NA
	NA	NA	(1.728)	(1.851)	NA	NA
$(P^A_i / B^W)_{t-1}$	NA	NA	NA	NA	-1.634	-2.482
	NA	NA	NA	NA	(1.793)	(1.868)
$Repre_i$	0.764*	0.741*	0.771*	0.753*	0.772*	0.985*
	(0.290)	(0.350)	(0.290)	(0.351)	(0.290)	(0.368)
$Learn1_{ti}$	2.520*	2.127*	2.511*	2.113*	2.513*	2.056*
	(0.312)	(0.332)	(0.312)	(0.332)	(0.312)	(0.336)
$Learn2_{ti}$	0.783*	1.183*	0.877*	1.175*	0.859*	1.172*
	(0.312)	(0.333)	(0.313)	(0.335)	(0.313)	(0.340)
% Correct						
All	84	86	84	86	84	87
In=1	78	81	72	81	88	81
In=0	88	89	88	89	78	90
Chi-Square	223	250	223	250	223	250
Fixed Eff.	No	Yes*	No	Yes*	No	Yes*
N[b]	420	420	420	420	420	420

[a] * and ** represent statistical significance at the 5 and 10 percent levels, respectively.
[b] Specifications 7, 8, 9, and 10 reflect all tenders except tenders 1 and 2. Specifications 11 and 12 do not include tenders 1 and 2, and 4, 6, and 16 due to the fact that winning bids were not available for tenders 3, 5 and 15, and tenders1 and 2 due to the lags on the learning variables.

in the Appendix.[5] Specifications 1, 3 and 5 use the hyperbolic learning index and vary across the treatment of prices. Specifications, 2, 4, and 6 mirror 1, 3, and 5 but include fixed effects. Specifications 7, 9, and 11 use lagged participation decisions to reflect the learning process and/or the stickiness in participation decisions. Specifications 8, 10, and 12 mirror those of 7, 9, 11 but include fixed effects.

All models are highly significant with chi-square statistics well in excess of critical values. All specifications do reasonably well in terms of overall classification rates, and in all cases, the models do a much better job of classifying firms that do not participate than firms that do participate. As might be expected, incorporation of firm specific effects helps to ameliorate this result but does not remove it. Finally, in all cases, firm specific dummies are jointly significant. Comparison of models with and without fixed effects suggest that the inclusion does not have a large impact on the outside option variable and dampens the effect of learning. However, inclusion does not remove the effect. These results confirm that firms are heterogenous in participation decisions.

The effect of representation is mixed. Only in specification 2 does the inclusion of fixed effects affect the statistical significance of the result. The price variables are of the correct sign [where included]. As the outside option becomes more attractive, firms are less likely to participate in the auction market. In all specifications containing our cumulative learning index (1-6) except specification 1, the variables reflecting outside options are statistically significant at

[5]The subset of firm dummies included in the specifications in table 1 were chosen through inspection and statistics, factoring in the robustness of the results along with the statistical import of the firm dummies. The subset varies across specification owing to differences in included observations i.e., tenders 4, 6 and 16 could not be included since in tender 3, 5, and 15 no winning bid was reported. Also, some specifications required lags outside of the sample range. The affected observations were omitted.

the 10 percent level. The exchange of the cumulative learning index with the lags of participation decisions, results in all price terms becoming statistically insignificant.[6]

Firms with representation are interpreted as having better information and/or reduced costs of executing trades, and as a result, are more likely to participate in the market. Having representation does not necessarily mean that the firm will participate in the market. In all specifications except specification 2, the effect of representation is highly significant in statistical terms, and, as we discuss below, the effect is substantial in economic terms.

Past participation in tenders appear to be a driving force in current participation decisions, reflecting the effects of learning. Our conjecture is that the effects of past participation are the result of familiarity with the market and, therefore, reflects learning and the costs associated with gaining familiarity in the market. In all cases, the coefficients have the correct sign suggesting that participation decisions are more likely with past decisions than without. In all specifications except specification 2, the coefficients on learning are statistically significant at the five percent level. Finally, consistent with the definition of the learning index in specifications 1-6 and consistent with the econometric results in specifications 7-12, the effects of learning dissipate. In specifications 1-6, the reciprocal of the cumulative sum forces the result and the effect of five past participation decisions lagged 10 periods (and none for the last 10 periods) is the same as the effect of five participation decisions in the last five periods.[7] In contrast, the lagged participation decisions in specifications 7-12 clearly indicates that the effect is much stronger for t-1 than t-2, suggesting that recent experience has the largest effect.

---

[6]These qualitative effects are consistent with the models containing the full set of dummies reported in the Appendix (table A-1).

[7]Such occurrences are not observed in the data but are presented to simply note a difficulty with the measure.

To illustrate the economic effects of the models, we present plots of probabilities against relevant variables, consisting of an outside option variable and a learning variable . In both cases, we use the coefficient estimates from specification 6.[8] The plots are based on average sample values for the other continuous variables and for firms with and without representation. Finally, we use the base firm results, i.e., all firm specific dummies are set to zero.

There are a number of striking results in Figure 1. First, the effect of the outside option is quite large. The outside option has a range of about 130 percent. Over this range, the probability of participation for a firm with representation falls from about .61 to about .28. For firms without representation, the probability falls from about .32 to about .10. Further, the range of values of the outside option (as indicated by the marks) is reasonably balanced, suggesting that price changes can and do materially affect participation from one tender to the next. The effect of representation is quite large with firms having representation being about twice or more likely to participate.

Figure 2 illustrates the effect of experience. The range of the data is quite large with firms that have no experience (none have experience in tender 2) to firms that participate in 25 of the 26 tenders. For all firms, the effects of cumulative experience are quite large. The differences in probabilities increase by more than a factor of the range of the data. For firms

[8] Of the specifications 1-6, specification 6 has the highest classification rate and seems to be better rooted in theory. Firms choose to participate based on expected profit if they win. The lagged price divided by the average winning bid seems to us as a better signal than the lagged price divided by the average bid. Regardless, the plots of the latter are quite comparable to those of the former, and do not materially affect the discussion. In specifications 6-12, the effect of outside options is not statistically significant. It may be that the lagged participation decisions contain part of the effect of outside options and mask the effect.

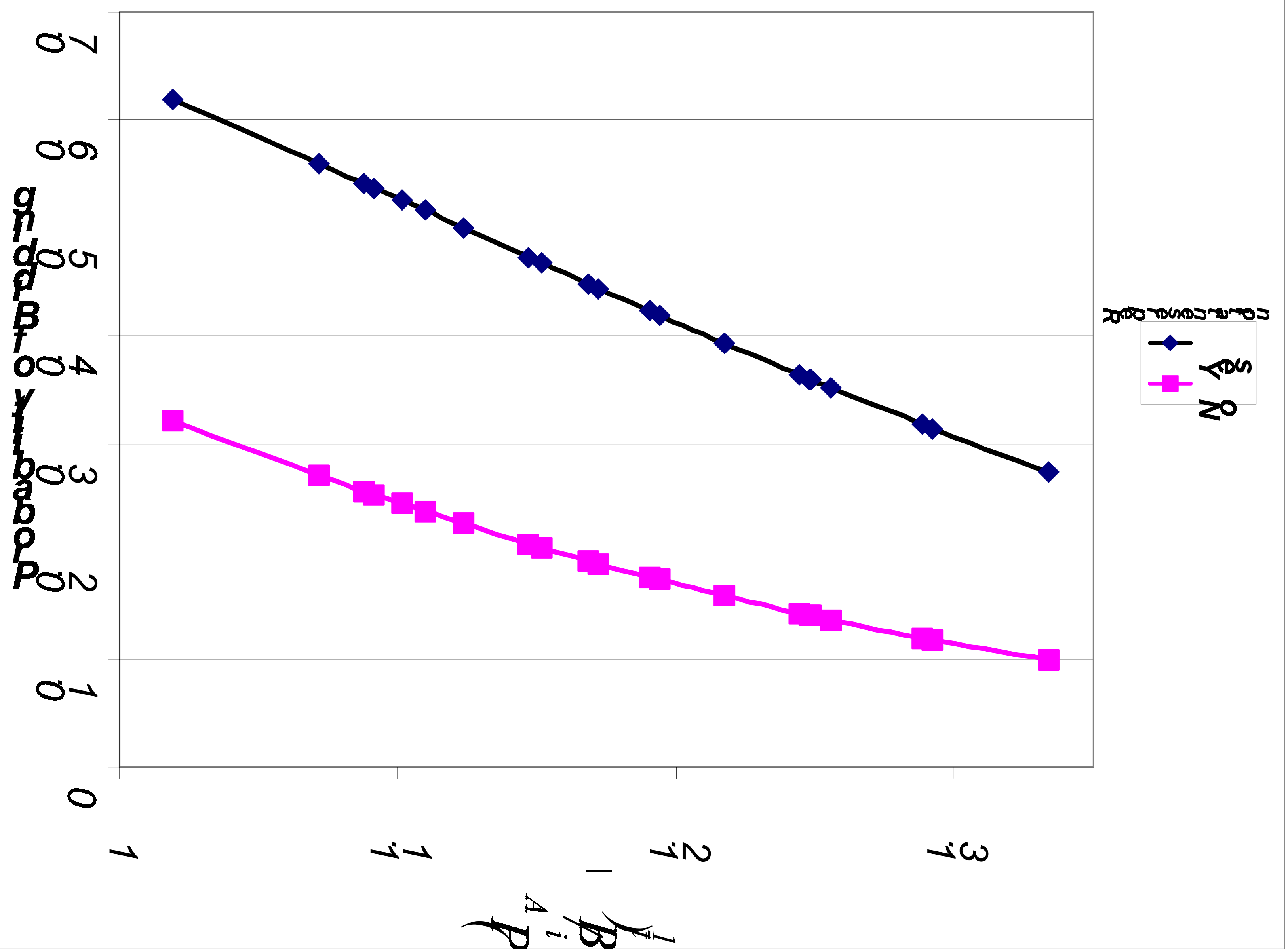

Figure 1. Impacts of Prices and Representation on Probability Bidding.

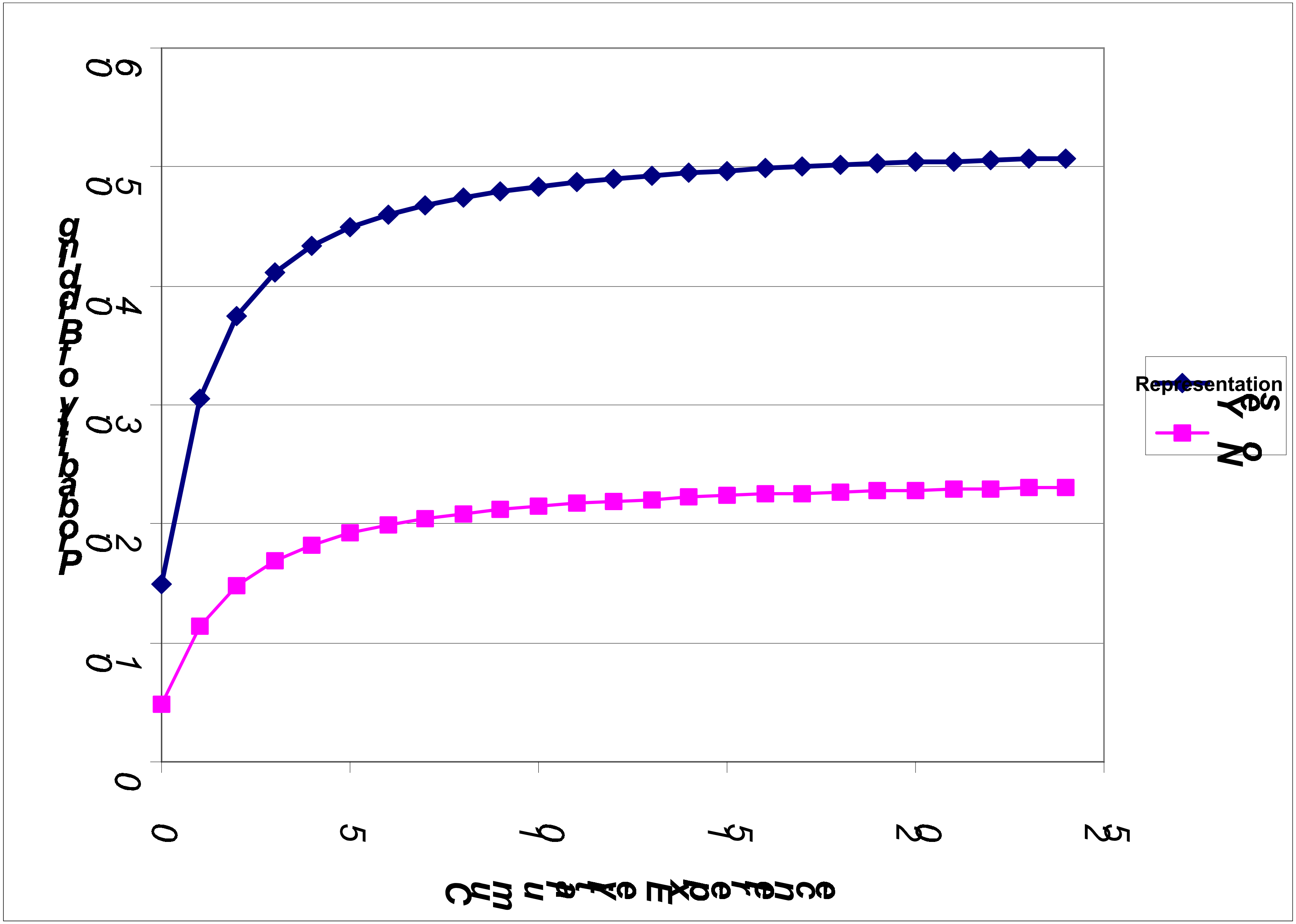

Figure 2. Effects of Experience on Bidding.

20

with no experience and no representation, the simulated probability is about .05 and increases up to about .22 as experience increases – a more than fourfold increase. For firms with no experience but with representation, the simulated probability increases from about .15 to more than .50 - a more than threefold increase. Most of the effect is reached within five or six tenders, suggesting a relatively fast learning rate. Over that time frame, learning occurs much faster for firms with representation than without. Finally, firms with representation are more likely to participate in a tender than those without. This effect runs from firms with representation being two to three times more likely to participate.

Bid Levels

We present results from several models explaining bid values. In all cases, there was no evidence of sample selection bias. That is, the unobserved variables in the participation decision do not seem to have a significant effect on bid levels. We present eight specifications in Tables 2 and 3 for the linear and double-log specifications, respectively. Models with no firm effects are shown in columns 1, 3, 5 and 7, while corresponding models with firm effects are shown in columns 2, 4, 6, and 8.

In all cases, inclusion of firm effects, representing unobserved and systematic differences across firms, is significant. In model 1, we estimate bids as a function of the outside option (the Rotterdam spot price). In models 3, 4, 7, and 8, we include information from the previous tender – the average winning bid. Inclusion of this variable simply reflects updating that may occur from the previous auction. Note, we experimented with alternative forms of updating such as the

Table 2. Bid Level Models: Linear Specification Estimates

Variable[a]	Model 1	2	3	4	5	6	7	8
Constant	6.363	7.849	-21.171**	-23.244**	7.342	3.558	-21.490**	-31.581*
	(8.211)	(8.592)	(11.045)	(11.854)	(8.200)	(9.199)	(10.931)	(12.940)
P^A	0.989*	0.994*	0.963*	0.961*	0.990*	0.998*	0.964*	0.969*
	(0.017)	(0.018)	(0.019)	(0.020)	(0.017)	(0.018)	(0.019)	(0.021)
B^W_{t-1}	.	.	0.085*	0.097*	.	.	0.091*	0.112*
	.	.	(0.024)	(0.025)	.	.	(0.024)	(0.025)
$Repre_i$	.	.	.	.	-2.013*	3.545	-3.256*	2.101
	.	.	.	.	(0.976)	(2.920)	(1.058)	(3.455)
$Learn_{it}$	.	.	.	.	-1.845	-3.039	-4.304**	-10.614*
	.	.	.	.	(1.910)	(2.166)	(-2.575)	(3.615)
R-Square	89	90	91	92	89	91	91	92
FE	No	Yes*	No	Yes*	No	Yes*	No	Yes*
N	397	397	332	332	397	397	332	332

[a] * and ** indicate statistical significance at the 5 and 10 percent levels, respectively.

Table 3. Bid Level Models: Log Specification Estimates

Variable[a]	Model 1	2	3	4	5	6	7	8
Constant	0.047	0.016	-0.308*	-0.375*	0.031	-0.037	-0.430*	-0.731*
	(0.1083)	(0.1128)	(0.1423)	(0.1528)	(0.1093)	(0.1167)	(0.1461)	(0.1715)
P^A	0.992*	0.999*	0.964*	0.963*	0.995*	1.005*	0.964*	0.977*
	(0.0175)	(0.0184)	(0.0201)	(0.0209)	(0.0176)	(0.0187)	(0.0197)	(0.0206)
B^W_{t-1}	.	.	0.086*	0.098*	.	.	0.105*	0.140*
	.	.	(0.0236	(0.0239)	.	.	(0.0239)	(0.0252)
$Repre_i$	.	.	.	.	-0.004*	0.008	-0.007*	0.0092
	.	.	.	.	(0.0020)	(0.0061)	(0.0022)	(0.0072)
$Learn_{it}$	.	.	.	.	0.001	0.002	0.008*	0.0084*
	.	.	.	.	(0.0011)	(0.0014)	(0.0014)	(0.0019)
R-Square	89	90	90	91	89	90	91	92
FE	No	Yes*	No	Yes*	No	Yes*	No	Yes*
N	397	397	332	332	397	397	332	332

[a] * and ** indicate statistical significance at the 5 and 10 percent levels, respectively.

ratio of the bid submitted and the winning bid from the last tender in which the firm participated, the ratio of the price and the winning bid from the last tender. The results reported dominate but (1/(1+cumulative participation decisions)) while in the log specifications we measure learning as (cumulative+cumulative participation decisions).

The fit of the models are quite high with R^2's ranging from .89 to .92. Comparisons of non-fixed effects specifications (1, 3, 5, 7) and fixed effect specifications (2, 4, 6, and 8) suggest that the addition of firm specific dummies increases only modestly the fit of the equations and affects the qualitative results only with respect to whether the firm has representation – the coefficient on *Representation* changes from negative and significant to insignificant with the addition of fixed effects.

Results suggest that the outside option is important. In almost all specifications the coefficient is less than one. The results are clear. If firms choose to participate, they submit bids which are competitive with the outside option, regardless of specification. The addition of the results from the last period auction improves fit modestly and is always statistically significant. Firms apparently observe the outcome
from the last tender and adjust their bids
accordingly. If, in the previous tender the winning bid is high, firms increase their bids. The magnitude is, perhaps, best judged from the double log specifications. If B^W_{t-1} increases by 10 percent, the bid submitted increases by about 1 percent.

Coefficients on firm representation are mixed and sensitive to inclusion of fixed effects. Inclusion of fixed effects are statistically significant at the 5 percent level. It appears that firms with representation tend to submit lower bids, *ceteris paribus*, but the lower bids are captured in the fixed effects and representation itself has no effect.

The findings with respect to learning are also mixed but only in terms of statistical significance. The results indicate that learning has either no influence (model 5 and 6) or a positive influence on bids (models 7 and 8). This likely indicates that firms with experience would shade their bids upwards, in part to avoid the winner's curse. In the linear specification, learning is measured as a hyperbolic function of past participation decisions. As a result it is an inverse measure where increased experience leads to a positive effect on the bid value. In all specifications, the effect is reasonably small. For example, using model 8 in the linear specification (the largest linear effect), an increase in experience from 9 to 10 tenders, increases the bid $[(-10.614)(-1)/(1+9)^2]=\$1.1/mt$. Results are comparable in the double log specification: a 10 percent increase in experience increases the bid by only .08 percent.

The effects within a given tender can be quite large. The range of results in the data is from zero to 24 tenders. In Figure 3, we plot the range of bid estimates for both the log and linear specifications (model 8, in both cases). While there are some differences across specification, some clear results emanate. First, the range of bids submitted by inexperienced bidders and experienced bidders is quite high, about $15 per ton. Second, while learning occurs throughout, most learning is complete after about five tenders (in the linear specifications). Apparently, with experience firms obtain some of the rents accruing to tender markets, while inexperienced firms tend to submit bids ensuring a win.

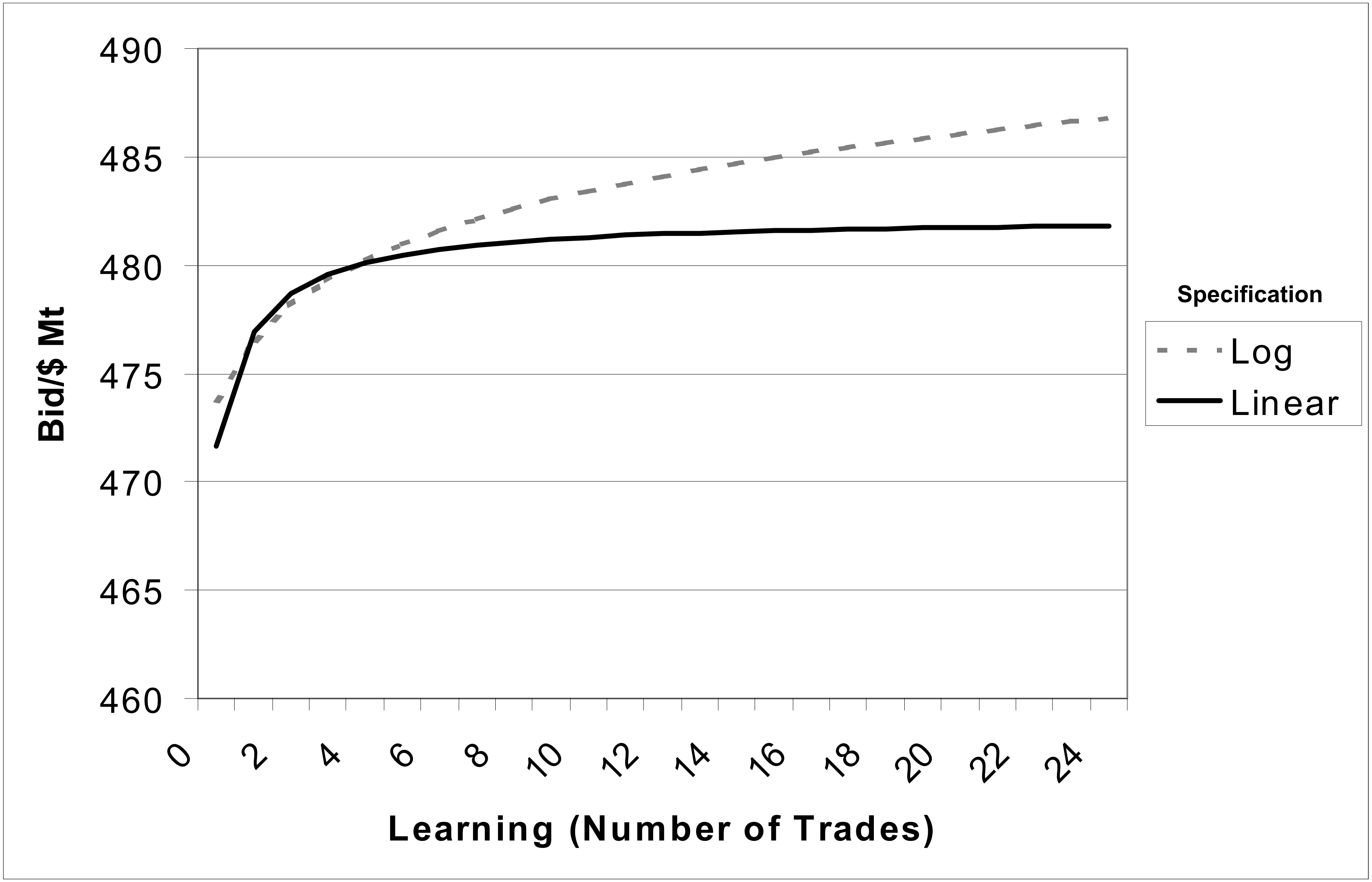

Figure 3. Effects of Learning on Bid Values

26

SUMMARY AND CONCLUSIONS

Reverse auctions are used extensively in agricultural marketing as procurement mechanisms. These age-old mechanisms have become revered in recent years as a result of information technology changes as well as the competitive environment among buyers and sellers. Reverse auctions are especially important and an interesting aspect of grain and oilseed importing where buyers use tenders to price their purchases, and determine suppliers for individual transactions. Understanding bidding strategies used by firms involved in auctions is critical to understanding the microstructure of competition in this sector and have important implications for buyers and sellers.

This paper developed models to analyze bidding strategies by international trading firms. There are two salient components of bidding strategies. One is the decision of whether to bid, and the other is how much to bid. These decisions are impacted by a multitude of factors. However, those of particular interest include the role and effects of learning, information and idiosyncratic firm characteristics.

There are a number of interesting results. Participation decisions are largely affected by information from previous tenders, learning and individual firm characteristics. Results from the previous tender have a positive impact on participation. High relative bids reflected in previous tenders induces greater participation. The learning curve effect is highly significant suggesting that firms have a tendency to learn from participating in previous tenders. This has a cumulative and nonlinear effect. Intuitively, these results suggest that learning has the effect of reducing unit costs as participation increases and most of the gains being achieved from the most recent experiences. This would imply that the expected payoff increases and as such greater cumulative participation has a positive impact on whether to bid. Another interesting variable is whether firms have representation in the importing country. In this case having representation nearly doubles the probability of bidding.

Bid value decisions are affected by the outside option (i.e., the alternative market), results from previous tenders and whether the firm has representation in the importing country. In addition, the effect of learning dissipates through time, seems to be important and has a positive impact on bid levels. The latter suggests experienced firms shade their bids upwards to mitigate impacts of the winner's curse. Finally, bidding strategies are highly predictable using readily available information. It appears the decisions to bid are independent of the decision on how much to bid.

These results have important implications for auction participants. The general goal of the buyer should be to increase the number of suppliers, their frequency of bidding and to keep them symmetrically informed. Though the buyer in this study has many suppliers, a notable aspect of competition is that their participation is quite random. Only a few are routinely involved in tenders. As a result, suppliers are likely not symmetric with respect to costs, or information. Consequently, one would expect a tendency for some to win more frequently than others. These results suggest there are two obvious implications for sellers. One is that expectations of rivals' bidding strategies, which are essential in determining own strategies, are predictable and should be explored. Second, both representation and experience enhances success in markets using these types of mechanisms.

This paper provides several contributions to the evolving literature on the empirical analysis of bidding strategies and auctions. It provides an understanding of the microstructure of firm conduct in industries dominated by bidding competition. Second, is the role and effect of learning in industries in which bidding is an integral pricing mechanism. The learning, or experience, curve effect has been an important foundation for business strategy, and has recently become the subject of empirical analysis. These results indicate that learning has very important impacts on the formulation of firms' bidding strategy which is consistent with other studies' findings that better informed bidders earn greater returns.

REFERENCES

Avery, C., and J. Kagel. 1997. "Second-Price Auctions With Asymmetric Payoffs: An Experimental Investigation." *Journal of Economics and Management Strategy* Vol. 6(3):573-603.

Battalio, R., Kogut, C. and D. Meyer. 1990. "The Effect of Varying Numbers of Bidders in First-Price Private Value Auctions," in L. Green and J. Kagel (eds), *Advances in Behaviorral Economics*, Vol 2 (Norwood, NJ, Ablex).

Bichler, M. 2001. *The Future of eMarkets: Multi-Dimensional Market Mechanisms*, Cambridge Press.

Brist, L., and W.W. Wilson. "Learning by Doing in DRAM Markets," working paper. University of Oregon, Department of Economics, Eugene.

Brown, K. C. 1969. *Bidding for Offshore Oil: Towards an Optimal Strategy*. Dallas, TX: Southern University Press.

Bourgeon, J., and Y. LeRoux. 2001. "Traders' Bidding Strategies on European Grain Export Refunds: AN Analysis with Affiliated Signals," *American Journal of Agricultural Economics,* (August 2001):83(3):563-575.

Bourgeon, J., and Y. LeRoux. 1996a. "Optimal Auction Theory and EC Grain Export." I. Sheldon and P. Abbott, ed., *Industrial Organization & Trade in the Food Industries*. Boulder, CO: Westview Press.

Bourgeon, Jean-Mark, and Yves LeRoux. 1996b. "Tenders for European Cereal Export Refunds: A Structural Approach." *European Review of Agricultural Economics* Vol. 23:5-26.

Cassady, R. 1967. *Auctions and Auctioneering*. Berkeley, CA: University of California Press.

Caves, R. 1977-78. "Organization, Scale, and Performance in the Grain Trade*, Food Research Institute Studies*, Vol. 16:107-123.

Capen, E. C., R. V. Clapp, and W. M. Campbell. 1971. "Competitive Bidding in High-Risk Situations." *Journal of Petroleum Technology* Vol. 23:641-653.

Cassady, R. 1967. *Auctions and Auctioneering*. Berkeley, CA: University of California Press.

Coy, P. "Going, Going, Gone...Sucker!: How 'winner's curse' could undermine online auctions." *Business Week*, (March 20, 2000):124-125.

Crampton, P. 1997. "The FCC Spectrum Auctions: An Early Assessment," *Journal of Economics and Management Strategy*, Vol. 6(3):431-497.

Crampton, P. 1995. "Money Out of Thin Air: The Nationwide Narrowband PCS Auction." *Journal of Economics & Management Strategy* Vol. 4(2):267-244.

Dutta, Prajit. 1999. *Strategies and Games: Theory and Practice*. Cambridge, MA: The MIT Press.

Dyer, Douglas, and John H. Kagel. 1996. "Bidding in Common Value Auctions: How the Commercial Construction Industry Corrects for the Winner's Curse." *Management Science* October(1):463-75.

Dyer, D., J. Kage, and D. Levin. 1989. "Resolving Uncertainty about Number of Bidders in Independent Private Value Auctions: An Experimental Analysis," *Rand Journal of Economics*, (20):268-279.

Engelbrecht-Wiggans, Richard. 1980. "Auction and Bidding Models: A Survey." *Management Science* Vol. 26:119-142.

Estey, W. 1998. *Grain Handling and Transportation Review: Final Report*. Report to the Honorable D. Collennette, Minister of Transport, Canada, Dec. http://www.grain.gc.ca.

Hausch, Donald B., and Lode Li. 1993. "A Common Value Auction Model with Endogenous Entry and Information Acquisition." *Economic Theory* Vol. 3:315-334.

Hughart, D. 1975. "Informational Asymmetry, Bidding Strategies, and the Marketing of Offshore Petroleum Leases." *Journal of Political Economy* Vol. 83(5):969-985.

Klemperer, Paul. 1999. "Auction Theory: A Guide to the Literature." *Journal of Economic Surveys* Vol. 13(3):227-286.

Kottas, J., and B. Khumawata. 1973. "Contract Bid Development for the Small Businessman." *Sloan Management Review* Vol. 14(Spring):31-45.

Kroeger, A. 1999. *Stakeholder's Report.* Letter to the Honorable D. Collennette, Minister of Transport, Canada, Sept. http://www.tc.gc.ca/railpolicy/kroeger .

Kuttner, R. 1996 *Everything for Sale: The Virtues and Limits of Markets*. Knopf Inc.

Latacz-Lohmann, Uwe, and Carel Van der Hamsvoort. 1997. "Auctioning Conservation Contracts: A Theoretical Analysis and an Application." *American Journal of Agricultural Economics* Vol. 79(May):407-418.

Lieberman, M. 1984. "The Learning Curve and Pricing in the Chemical Processing Industry," *Rand Journal of Economics*, (Summer):213-228.

Lilien, Gary L., and Philip Kotler. 1992. *Marketing Models.* Englewood Cliffs, NJ: Prentice-Hall.

McAfee, R. P., and J. McMillan. 1987. "Auctions and Bidding." *Journal of Economic Literature* (June)25:699-738.

McAfee, R. P., and J. McMillan. 1986. "Bidding for contracts: a principal-agent analysis." *Rand Journal of Economics*. 17(3):326-338.

McAfee R. P., and J. McMillan. 1996. "Analyzing the Airwaves Auction." *Journal of Economic Perspectives* Vol. 10(1)Winter:159-175.

McAfee, R. P., and J. McMillan. 1996b. "Competition and Game Theory," *Journal of Marketing Research.* Vol. 33(August):263-267.

McMillan, J., M. Rothschild, and R. Wilson, 1997. "Introduction," *Journal of Economics and Management Strategy*, Vol. 6(3): 425-431.

McMillan, J. 1994. "Selling Spectrum Rights" *Journal of Economic Perspectives,* Vol. 8(3):145-62.

McMillan, J. 1997. "Introduction," *Journal of Economics and Management Strategy,* Special Issue title Market Design and the Spectrum Auctions. Vol. 6(3):425-30.

Milgrom, Paul. 1985. "The Economics of Competitive Bidding, A Selective Survey," in L. Jurwicz, D. Schmeidler and H. Sonnenschein (Eds.) *Social Goals and Social Organizations*. Cambridge, UK: Cambridge University Press, pp. 216-289.

Milgrom, Paul. 1987. "Auction Theory," in Truman Bewley (ed.) *Advances in Economic Theory*:Fifth World Congress. Cambridge, UK: Cambridge University Press.

Milgrom, P. 1989. "Auctions and Bidding: A Primer." *Journal of Economic Perspectives*. Vol. 3(3):3-22.

Molho, I. 1997*. The Economics of Information: Lying and Cheating in Markets and Organization,* Malden, MA: Blackwell Publishers.

Monroe, Kent B. 1990. "Developing Competitive Bids." Chapter 17 in *Pricing: Making Profitable Decisions*. New York, NY: McGraw-Hill.

Nagle, T., and R. Holden. 1994. "Pricing with uncertainty: Techniques for analyzing complex pricing decisions." *The Strategy and Tactics of Pricing: A Guide to Profitable Decision Making*, 2nd Edition. Englewood Cliffs, NJ: Prentice Hall.

Norton, R. 1995. "Winning the Game of Business," *Fortune*, 131(2):36.

Oster, S. 1994. Modern Competitive Analysis, 2nd Edition, Oxford.

Phlips, Louis. 1988. *The Economics of Imperfect Information*. New York: Cambridge University Press. pp. 281.

Porter, R. and J. Zona, 1999. "Ohio school milk markets: An analysis of bidding, *Rand Journal of Economics*. 30(2):263-188.

Oren, S. S. and M. H. Rothkopf, "Optimal Bidding in Sequential Auctions," Operations Research, V. 23, No. 6 (1975):1080-1090.

Rasmusen, E. 1989. *Games and Information: An Introduction to Game Theory*. Cambridge, MA:. Basil Blackwell, Inc.

Reece, Douglas K. 1978. "Competitive Bidding for Offshore Petroleum Leases." *Bell Journal of Economics.* (Autumn): 369-384.

Rothkopf, M. H., and R. M. Harstad. 1994. "Modeling Competitive Bidding: A Critical Essay," *Management Science.* Vol. 40(3):364-384.

Rothkopf, M.H. 1991. "On Auctions with Withdrawable Winning Bids." *Marketing Science*. 10(1):40-57.

Rothkopf, M.H. and R.M. Harstad. 1994. "Modeling Competitive Bidding: A Critical Essay." *Management Science*. 40(3): 364-384.

Rampton, Roberta. 1999. "CWB not tiled by new Japanese tendering system." *The Western Producer*. Modern Press, Saskatoon, (July 8):15.

Rasmusen, Eric. 1994. *Games and Information: An Introduction to Game Theory*, 2nd Edition. Cambridge, MA: Basil Blackwell, Inc.

Rothkopf, M. H., and R. M. Harstad. 1994. "Modeling Competitive Bidding: A Critical Essay." *Management Science.* Vol. 40(3) March:364-384.

Salanie', B., 1997. The Economics of Contracts. Cambridge, MA: The MIT Press.

Sewall, M. 1976. “A Decision Calculus Model for Contract Bidding.” *Journal of Marketing.* Vol. 40(October):92-98.

Shogren, J. J. List, and D. Hayes. 2000. “Preference Learning in Consecutive Experimental Auctions,” *American Journal of Agricultural Economics*. 82(4):1016-1021.

Simon, H. 1989. *Price Management*, Amsterdam: Elsevier Science Publishers.

Thaler, R.H. *1992. The Winner’s Curse: Paradoxes and Anomalies of Economic Life*. Princeton, NJ: Princeton University Press.

The Economist. 2000. “What am I Bid?” *The Economist.* (May 6):80.

Wilson, R. 1988. “Introductory Note: Trading Procedures,” In *Analytical Foundations of Pricing Strategy*. Stanford, CA: Stanford Business School. Version 10, 362-N2, September.

Wilson, R. 1992. “Strategic Analysis of Auctions.” Chapter 8 in *Handbook of Game Theory with Economic Applications* Vol. 1:228-279, Edited by Robert Aumann and Sergiu Hart. North Holland, Amsterdam.

Wilson, W. W., and B. L. Dahl. 1999. *Transnational Grain Companies: Evolution and Strategies in North America*. Ag. Econ. Rpt. #412, Fargo: North Dakota State University, Department of Agricultural Economics.

Wilson, William W., S. Priewe, and Bruce Dahl. 1998. “Forward Shipping Options for Rail: A Strategic Risk Anaylsis .” *J. of Agr. and Resource Econ.* 23. No. 2(1998):526-544.

Appendix

Table A-1. Participation Decision Coefficient Estimates

	Model[b]					
Variable[a]	1	2	3	4	5	6
Constant	1.619	2.736**	2.402	2.142	4.844**	4.640*
	(1.273)	(1.511)	(1.369)	(1.559)	(1.740)	(2.017)
P^A	-.003	-0.005**	NA	NA	NA	NA
	(0.002)	(0.003)	NA	NA	NA	NA
$(P^A_i / \bar{B})_{t-1}$		NA	NA	-2.051**	-2.475**	NANA
	NA	NA	(1.164)	(1.310)	NA	NA
$(P^A_i / B^W)_{t-1}$		NA	NA	NA	NA	
	-4.141*	-4.672**				
	NA	NA	NA	NA	(1.452)	(1.669)
$Learn_{it}$	-1.983*	-0.37	-2.711*	-1.797*	-2.706*	
-1.737*						
	(0.311)	(0.433)	(0.387)	(0.510)	(0.425)	(0.570)
$Repre_i$	1.006*	-0.52	1.031*	0.869	1.075*	0.927
	(0.204)	(0.605)	(0.215)	(0.577)	(0.230)	(0.619)
% Correct						
all	69	77	71	79	72	81
In=1	47	65	48	66	55	67
In=0	84	84	83	87	82	89
Chi-Square	94	221	117	219	104	205
Fixed Effects	No	Yes	No	Yes	No	Yes
N[c]	520	520	500	500	440	440

[a] * and ** represent statistical significance at the 5 and 10 percent levels, respectively.
[b] Specifications 1 and 2 reflect all the data; Specifications 3 and 4 require the omission of the first tender, consisting of 20 firms, Specifications 5 and 6 require the omission of tenders 1, 4, 6, and 16 due to the fact that winning bids were not available for tenders 3, 5 and 15, and tender 1 did not have a preceding tender.

Table A-1. (Continued)

Variable[a]	Model[b] 7	8	9	10	11	12
Constant	-1.095	-0.438	-2.424	-1.432	-0.599	0.747
	(1.684)	(1.839)	(1.700)	(1.826)	(2.139)	(2.287)
P^A	-0.002	-0.003	NA	NA	NA	NA
	(0.003)	(0.003)	NA	NA	NA	NA
$(P^A_i / \bar{B})_{t-1}$	NA	NA	-0.058	-0.734	NA	NA
	NA	NA	(1.431)	(1.504)	NA	NA
$(P^A_i / B^W)_{t-1}$	NA	NA	NA	NA	-1.634	-2.632
	NA	NA	NA	NA	(1.793)	(1.891)
$Repre_{ti}$	0.735*	0.400	0.741*	0.441	0.772*	0.595
	(0.270)	(0.675)	(0.269)	(0.667)	(0.290)	(0.713)
$Learn1_{ti}$	2.298*	1.874*	2.299*	1.869*	2.513*	2.005*
	(0.285)	(0.305)	(0.284)	(0.306)	(0.312)	(0.340)
$Learn2_{ti}$	1.460*	1.039*	1.457*	1.033*	1.172*	0.704*
	(0.285)	(0.312)	(0.284)	(0.313)	(0.313)	(0.347)
% Correct						
All	83	86	83	86	84	87
In=1	73	80	73	80	88	81
In=0	89	89	89	90	78	90
Chi-Square	253	289	252	288	223	259
Fixed Eff.	No	yes	No	Yes	No	Yes
N[c]	480	480	480	480	420	420

[a] * and ** represent statistical significance at the 5 and 10 percent levels, respectively.
[b] Specifications 7, 8, 9, and 10 reflect all tenders except tenders 1 and 2. Specifications 11 and 12 do not include tenders 1 and 2, and 4, 6, and 16 due to the fact that winning bids were not available for tenders 3, 5 and 15, and tenders1 and 2 due to the lags on the learning variables.