Supplier Learning in Repeated Online Procurement Auctions

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Extended Abstract Submitted to WISE 2006

1. Introduction

Repetition is the key aspect of online procurement auctions as they are often conducted yearly or quarterly or even daily (Elmaghraby 2006; Pinker and et al. 2003). Yet it remains unknown (1) what the suppliers' incentives are for repeatedly participating in reverse auctions, especially for those non-winning suppliers (e.g. Jap 2002); (2) In business practice, whether suppliers learn how to bid or they actually have a "short memory".[2]

While procurement auction theorists suggest that, by participating in sequential auctions, suppliers may learn critical competitive information about their environment and react accordingly (e.g. Fevrier 2003; Jeitschko 1998), their predictions are mixed, however. For example, Fevrier (2003) shows numerically that the winner of the current auction should bid higher than the losers in the subsequent auction, contrary to the prediction of Luton and McAfee (1986). On the other hand, despite their prevalence in business practice, auction theory has been silent about the bidding dynamics both within and between auctions (Elmaghraby 2006). In sum, there is a pressing need of empirical investigations of repeated online procurement auctions, both for theory building and practical applications.

The objectives of this study are to empirically investigate: (1) the impact of information learned – rank order and lowest final bid - between successive auctions; (2) whether suppliers bid adaptively between two successive auctions, if so, the impact of rank information.

Via a detailed institutional analysis of a unique set of real-world repeated procurement auction data, we find: (1) Top ranked suppliers tend to bid less compared to low ranked suppliers in auction; Supplier's final bid in successive auction increases as the difference between its own bid and the lowest bid increases at the previous auction. (2) Suppliers do bid adaptively between two successive auctions; further such adaptive bidding behavior is mediated by their rank information.

2. Background and Hypotheses

There is a rich and growing theoretical literature on sequential auctions. Specifically, there has been an increasing attention on the information transmission and learning in recurring auctions (e.g. Fevrier 2003; Jeitschko 1998; Von der Fehr and Riis 2003). The models studied in Von der Fehr and Riis (2003) and Fevrier (2003) are closer to the sourcing and procurement process of ours. This process can be illustrated in Figure 1. A buyer wants to procure Q units of a good in each of two periods. The same set of $N > 2$ suppliers compete for the purchasing contract in both periods. Let b_{t-1}^{i} and b_{t}^{i} denote supplier i's final bids in the two periods respectively. Assuming there is no capacity or budget constraint in either period, we can normalize $Q = 1$. At the end of the first auction, suppliers know about their own rank orders r_{t-1}^{i} [3] and the lowest bid price b_{t-1}^{L}.

Drawing from the aforementioned analytical analysis, we estimate the following econometric model:

$$\log(b_t^i / b_t^{i-1}) = \alpha + \beta_1 r_{t-1}^i + \beta_2 \log(b_{t-1}^i / b_{t-1}^L) + \beta_3 \text{Controls} + \varepsilon_i \quad (1)$$

[1] If accepted, D.J. Wu will present this work.
[2] Source: private communication with an industry expert in strategic sourcing.
[3] r_{t-1}^{i} =1,2,3,4,…N with r_{t-1}^{i} =1 represents the lowest bidder, i.e. the highest rank.

where $\log(b_{t-1}^{i} / b_{t-1}^{L})$ is used to measure the difference between supplier *i*'s bid at auction *t-1* and the market price so as to overcome the issue that the purchasing contracts in our data set are non-identical. We make the following conjecture on the pattern of prices in repeated procurement auctions:

H1a: $\beta_1 < 0$.

H1b: $\beta_2 > 0$.

Hypothesis H1a implies that higher ranked suppliers tend to bid less compared to lower ranked suppliers in auction *t*, i.e. supplier *i*'s final bid b_t^i in auction *t* increases as r_{t-1}^i decreases. H1b suggests that supplier *i*'s final bid b_t^i in auction *t* increase as the difference between its own bid b_{t-1}^i and the lowest bid b_{t-1}^L at auction *t-1* increase.

To our best knowledge, there has not been any study on the changes in suppliers' bidding dynamics in repeated procurement auctions. However, studies on B2C auctions have shown the difference in bidding behavior between experienced and inexperienced bidders (Roth and Ockenfels 2006). They suggest attribute the discrepancy to bidders' learning better bidding strategies that are associated with higher winning probability and consumer surplus. Since the stake of B2B auctions is much higher than that of B2C auctions, suppliers should have more motivation to learn about how to bid. Therefore, we conjecture that:

H2a: Suppliers bid adaptively between two successive auctions.

H2b: Suppliers' adaptive bidding behaviors are mediated by their rank information (r_{t-1}^i *).*

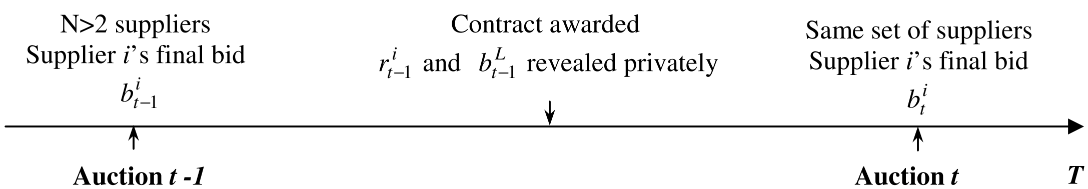

Figure 1: Sequential procurement auctions

3. Data

We obtained an online procurement auction data set from a major buyer in the high-tech industry. These data record the procurement activities of the buyer from year 2001 to 2004. The data set covers the entire bidding history for each auction, including auction number, supplier number, item number, supplier name, bidding time, unit price, total price and quantity for each supply item, among others. From the data set, we select 227 purchasing contract auctions with each one of them has been repeated for at least once. In total, 69 suppliers bid repeatedly for a subset of these contracts. If a supplier bids in two successive auctions, its bids from both of the auctions form one single data point. The selection method produces a sample of 693 data points for our empirical analyses.[4]

4. Results

4.1. Rank Order and Lowest Bid

While testing hypotheses H1a and H1b, we control for the number of repeating suppliers and other suppliers, as well as the year dummies. The results are presented in Table 1. Model I uses robust Ordinary Least Square (OLS) estimator and excludes year dummy variables. The coefficients support both hypotheses H1a and H1b. The negative coefficient for r_{t-1}^i indicates that when supplier *i* is one of the top

[4] We remove the auctions that have less than 3 suppliers to fulfill the assumption of theoretical studies in the literature.

bidders, $\log(b_t^i / b_{t-1}^i)$ increases. In other words, supplier *i*'s bid in auction *t* is less aggressive than that of lower ranked suppliers**.** Furthermore, the positive coefficient for $\log(b_{t-1}^i / b_{t-1}^L)$ implies that when supplier *i* is not cost efficient, i.e. its bid b_{t-1}^i is much higher than the market price as signaled by b_{t-1}^L**,** the bid of the supplier tends to be higher in the following auction *t*.

Table 1: Regression of price ratio of successive auctions on rank order and lowest bid

	Model I	**Model II**	**Model III**	**Model IV**
	$\log(b_t^i / b_{t-1}^i)$	$\log(b_t^i / b_{t-1}^i)$	$\log(b_t^i)$	$\log(b_t^i)$
r_{t-1}^i	-0.0918***	-0.0868***	-0.0819***	-0.0744***
$\log(b_{t-1}^i / b_{t-1}^L)$	0.0495*	0.0284	0.0751**	0.0526**
$\log(b_{t-1}^i)$			0.9235***	0.9145***
Num. of repeating suppliers	0.0240	0.0051	-0.0023	-0.0280
Num. of other suppliers	-0.0613**	-0.1034***	-0.0727***	-0.1268***
year2002		-0.0850*		-0.1992***
year2003		0.1991***		0.1670**
year2004		-0.0518		-0.1363
Constant	0.1309	0.1994**	0.3599***	0.5479***
Observations	693	693	693	693
R^2	2.6%	4.1%	86.5%	86.9%

Notes: * p<0.1 ** p<0.05 ***p< 0.01.

When we add year dummy variables in the Model II, the coefficient of year 2002 and 2003 are significant but opposite signs. At the same time, coefficient of $\log(b_t^i / b_{t-1}^i)$ is not significant anymore. It seems the changes in the industry have a stronger impact. Moreover, the number of repeating suppliers is not significant. On the other hand, an increase in the number of other suppliers drives down suppliers' bids. Model III and IV are unconstrained model of Model I and II. Results of these models are consistent with each other.

4.2. Adaptive Bidding Behavior

Following Zhong and Wu (2006), we use four constructs to abstract bidding behavior for the auctioning of a procurement contract: time of entry, time of exit, number of bids and average rank order. We then take a two-step approach[5] to estimate the transition of bidding strategies in two successive auctions. First, we apply LC cluster analysis to classify bidding behavior. In the second step, we estimate a Latent Markov (LM) model to correct measurement errors in the first step. The LM has the form as shown in Figure 2. Let B_{t-1} and B_t denote the vectors of the bidding strategies in auctions *t-1* and *t* respectively. Let R_{t-1} denote a dummy variable indicating whether a supplier is among the top two bidders at the end of auction *t-1*. The joint distribution of the three variables $\pi_{b_t b_{t-1} r_{t-1}}$ can be decomposed into a set of conditional probabilities:

$$\pi_{b_t b_{t-1} r_{t-1}} = \pi_{b_{t-1}} \pi_{b_{t-1} r_{t-1}} \pi_{b_t | b_{t-1} r_{t-1}} \qquad (2)$$

Therefore $\pi_{b_t b_{t-1} r_{t-1}}$ can be estimated by specifying a set of logit models for the conditional probabilities. Our focus is the conditional probability $\pi_{b_t | b_{t-1} r_{t-1}}$, which is the probability of bidding b_t at auction t, given

[5] Our small sample size prevents us to use the strategic variables directly to form the dynamic model.

the supplier's bidding strategy b_{t-1} in the previous auction and the corresponding outcome r_{t-1}. Using a logit formulation, $\pi_{b_t|b_{t-1}r_{t-1}}$ can be expressed as:

$$\log\left(\frac{\pi_{b_t|b_{t-1}r_{t-1}}}{1-\pi_{b_t|b_{t-1}r_{t-1}}}\right) = \beta_1^{'} X_{B_t} + \beta_2^{'} X_{B_t B_{t-1}} + \beta_3^{'} X_{B_t R_{t-1}} + \varepsilon \qquad (3)$$

where X_{B_t} is a vector of the bidding strategies in auction *t*; X_{IJ} are vectors of the combination of variable *I* and *J*. For example, $X_{B_t B_{t-1}}$ is a vector of the combination of the bidding strategies at both auctions *t-1* and *t*. With this a model, we can estimate the changes in bidding strategies, and more importantly, the impact of the outcome of the first auction on suppliers' bidding behavior at the second auction.

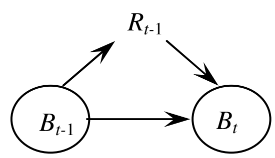

Figure 2: Latent Markov model with rank order information

The first step reveals five bidding strategies that are consistent with the findings in Zhong and Wu (2006), namely, Non-strategic bidding, Participator, Early-evaluator, Mid-evaluator and Opportunist. The discovered strategies formed the set of bidding patterns for B_{t-1} and B_t.[6]

Utilizing the results from the first step, we next estimate the LM model following the method in Vermunt et al. (1999). Figure 3 shows the estimated transitional probabilities without the effect of auction outcome R_{t-1} from the LM analysis. In general, a Participator is more likely (0.44, $p < 0.05$) to retain the same bidding strategy in the second auction event. Zhong and Wu (2006) shows that Participator is more likely to win a contract compared to other bidding strategies. Therefore, the high probability transition we obtained here is reasonable given the high probability of earning the contracts. By the same token, Early-evaluator, Mid-evaluator, and Opportunitist bidders, when they are the lowest bidder of the current auction, tend to shift to use the bidding strategy of Participator in the next auction event, to increase the probability of winning the deal. In sum, the LM analysis reveals initial evidence of changes in bidding behavior in sequential procurement auctions.

Moreover, including the coefficients for $X_{B_t R_{t-1}}$, we can compute the transition probability conditional on the auction outcome R_{t-1}, rank order information of a supplier after the auction *t-1*, as shown in Table 2. Each row represents the bidding strategy at auction *t-1* and two possible outcomes: being a high ranked supplier vs. a low ranked supplier. Each column represents a bidding strategy at auction *t*. In sum, being whether a high or low ranked supplier after auction *t-1* mediates the adaptive bidding behavior across auctions.

Taking together, we conclude that our latent Markov model analysis evident adaptive bidding behavior in successive auction. Overall, at the strategy level, suppliers' dynamic bidding strategies seem to follow a pattern of "win-stay-loose-shift" over time.

Summary

The novelties, to the best of our knowledge, of this work are the following: we show that information learned – rank order and lowest final bid - between auctions have a significant impact on suppliers' final

[6] Due to their sparseness, Non-strategic bidding is dropped in the second step.

bids; (2) within auctions, we uncover bidding patterns and between auctions, suppliers learn to bid adaptively, utilizing rank information obtained from previous auctions.

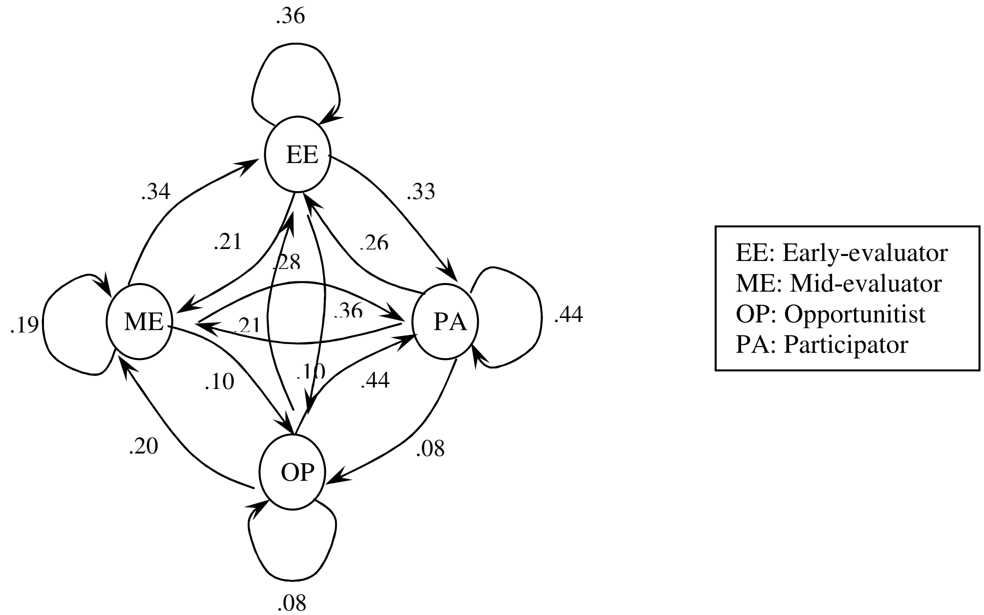

Figure 3: LM model analysis reveal evidence of adaptive bidding behavior. Suppliers' dynamic bidding strategies seem to exert a "Win-Stay-Loose-Shift" pattern.

Table 2: Transition probability mediated by rank order information

			Auction *t*			
			Early-evaluator	Mid-evaluator	Participator	Opportunist
Auction *t-1*	Early-evaluator	Low rank	0.3925	0.1869	0.3178	0.1028
		High rank	0.2143	0.2857	0.3929	0.1071
	Mid-evaluator	Low rank	0.3525	0.1721	0.3607	0.1148
		High rank	0.3125	0.2813	0.3438	0.0625
	Participator	Low rank	0.3011	0.1935	0.3656	0.1398
		High rank	0.2474	0.2216	0.4742	0.0567
	Opportunist	Low rank	0.5000	0.1667	0.2778	0.0556
		High rank	0.2075	0.2075	0.4906	0.0943

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