COMPETITIVE BIDDING STRATEGY
IN BUYER-DETERMINED
ONLINE REVERSE AUCTIONS

Ernan Haruvy
School of Management
University of Texas at Dallas

Sandy Jap
Goizueta Business School
Emory University

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Abstract

Many industries utilize competitive, online reverse auctions for industrial procurement. In many of these auctions, the lowest price bidder is not guaranteed to be the winner and the buyer has full latitude to select the winner from any of the qualified bidders. What are the competitive bidding strategies of bidders in these online auctions? Using an adaptive hierarchical bounded rationality mixture model framework and point-by-point bid data from ten lots of industrial reverse auctions, we find that some bidders incorporate quality information from competitive bids over the course of the auction; that is, suppliers not only adjust their bids for their own quality-advantage or disadvantage – they also account for opponents’ perceived quality differences (on the basis of anonymous price bids). This behavior has implications for the optimal choice of auction format. We estimate bidder rationality from the data and use the estimated parameters to then examine predictions for artificial adaptive agents under different assumptions. We find that the choice of a full price visibility auction design versus a partial price visibility format critically depends on the relationship between cost and quality as well the number of competing sellers.

Keywords: Auctions, Procurement, Learning

JEL Classification: D44; D83

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1. Introduction

As interorganizational processes at the boundaries of the firm become increasingly digitized, new forums for competitive dynamics in the sourcing process have emerged. Specifically, online reverse auctions, in which sellers bid prices down, is a widely used practice (Fuller 2004) across a wide range of industries ranging from manufacturing, agricultural, and government and defense sectors to consumer products, services, pharmaceutical, and high-tech industries. The main impetus for the use of these online auctions is price savings (Tully 2000; Cohn 2000) and the use of these auctions is growing (Beall et al 2003). Academic interest in online reverse auctions is also on the rise, with growing streams of research on their benefits and risks (Mabert and Skeels 2002; Smeltzer and Carr 2003; Bandyopadhyay, Barron, and Chaturvedi, 2005) as well as the performance implications of auction design choices (Che, 1993; Branco, 1997; Chen-Ritzo at al., 2006).

IT-enabled procurement auctions gives rise to novel forms of bidding competition and strategies. For example, in many procurement settings, buyers must consider important non-price factors such as product quality supplier responsiveness and capabilities, etc.. Hence, many industrial buyers rely on “buyer-determined” full-price visibility auctions in which suppliers own qualities are known, but competitor qualities and identities are unknown. Only price bids, which are a non-guarantor of winning, is visible to all bidders and this information is constantly changing over the course of the auction. In addition, the buyer has full latitude to select the winner on any basis (Jap 2002; Engelbrecht-Wiggans et al., 2006). While this format enables buyers to consider an array of non-price attributes in its selection decision, it also opens the door for new bidding strategies on the part of suppliers. If the lowest price bidder is not guaranteed the win, suppliers lose the incentive to bid down to their costs, which is the dominant bidding
strategy in English auctions (McAfee and McMillan, 1987). What bidding strategies might suppliers use in these auctions? How does this context impact the nature of competitive bidding that arises? And how do variations in this digitized context (e.g., differences in the amount of information regarding the nature of the price bids) alter the nature of competition? The answers to these questions speak to the goal of the Special Issue and hold important implications for the buyer’s design of procurement auctions. Effective auction design can constitute a key strategic choice of the firm, as noted by economist Hal Varian:

Designing the right kind of auction will have as big an impact on the brand, customer loyalty, and profit margins of the undertaking as will the designing of the right kind of products. (Schrage 2000).

In this research, we take an initial step toward illuminating our understanding of competitive bidding strategies in this online reverse auction format. Specifically we propose that the goal of the bidder is to remain in the buyer’s consideration set in accordance with their non-price attributes (i.e., quality) as opposed to their costs. Thus, each bid depends on the bidder’s privately known quality and inferences of the competition’s quality from the bids observed over the course of the auction, creating a dynamic adjustment process that requires continuous updating of beliefs regarding other bidders’ qualities. To this end, we develop an analytical model of how bidders use information from observed bids by others and then estimate the degree of information use by bidders via the use of point-by-point bid data from ten online reverse auction lots for metal parts and plastics. Specifically, we first assess the extent to which bidders adjust their bids for known and perceived quality differences and find that bids are adjusted according to what bidders believe the quality level of their competition might be. That is, a high quality supplier will not bid aggressively against what are likely to be low quality suppliers, but will remain competitive with the bids of those it perceives to be similar high quality suppliers.
In order to study the implications of this finding for auction design, we then use a simulation analysis with artificial adaptive agents (e.g., Andreoni and Miller 1995) to make forecasts about buyer surplus and price in these online auctions. The adaptive agents are either sophisticated or naïve bidders, referring to the extent to which they utilize price data. Buyers can vary the auction format by truncating the price information revealed to the bidders. Since a bidder might partially deduce the quality of its competition in a full price visibility format, a buyer could limit that ability by truncating bids that are above the minimum and showing the minimum price at any given point without attributing the lowest price to any one seller. This is a common format, which we refer to as “partial visibility” (Jap, 2007).

Hence, we consider the buyer’s preference for auction format as a function of the relationship between cost and quality and the number of bidders, two common pillars of auction design research (see McAfee and McMillan 1987 for a review and Bapna, Jank and Shmueli, 2008). We find that when the relationship between product cost and quality is positive (negative), the partial price visibility format is better (worse) for the buyer; with “better” referring to the buyer surplus, or value minus price paid. However, when there are few bidders in the event, the buyer is better off utilizing a full price visibility format and when there are many bidders, a partial price visibility format is better for the buyer.

Together, we are able to make several contributions to our understanding of bidding behavior in dynamic procurement auctions: (1) We propose a theoretical framework to characterize dynamic bidding behavior with hierarchical boundedly rational agents. (2) We propose an econometric framework that follows our theoretical framework and applies a mixture model approach to account for different hierarchies of rationality. (3) We estimate our econometric model on real procurement data and find support for the theory. We are able to
show that suppliers are sensitive to competitors’ qualities implied by their bids. This is a useful step in moving from previously investigated dynamic settings in which qualities are observed (Asker and Cantillon, 2008; Chen-Ritzo at al., 2005) to more realistic settings in which qualities are only inferred. (4) We use our estimated parameters and qualities to make recommendations regarding optimal auction formats. Since the data come from one auction format, we study artificial adaptive agents to gain insights about alternative formats, an approach which has been previously used in the literature (e.g., Herbert 1999; Consiglio and Russino 2007; Duffy and Unver 2007).

In the sections that follow, we describe the auction setting (section 2) and develop a model of how bidders use information from observed bids by others (section 3). We derive hypotheses based on the model (section 4). We then describe the empirical investigation (section 5). We conclude with a discussion of key insights, limitations, managerial implications and directions for future research.

2. The Online Reverse Auction Process

There are numerous papers that describe the online reverse auction process in great detail from preliminary steps to contract awards (e.g., Emiliani 2000, Mabert and Skeels 2002, Stein Hawking and Wyld 2003). In general, the buyer will issue a request for purchase to a set of suppliers that details the nature of the purchase contract as well as product, delivery, and handling specifications and expectations. Then, the buyer will invite a set of prequalified\textsuperscript{1} suppliers to bid in an online auction for the opportunity to win the contract. The auction may be designed and executed by the buyer or in many cases, as in the present data, the auction process

\textsuperscript{1} Prequalification procedures might include site visits, research, extensive surveys on capabilities and manufacturing processes, or other buyer designed, quality inspection processes.
is conducted by a third party auctioneer who informs the suppliers of the event rules such as: (i) the buyer can select a winner on any basis; the lowest bid is not guaranteed to win the contract\(^2\), (ii) the sourcing manager is prohibited from bidding against suppliers in the auction (a practice known as “shilling”), (iii) all competitors are viable pre-qualified sourcing options for the buyer, and (iv) supplier bids are legally binding. The suppliers are not told who their competitors are or how many suppliers would bid against them.

The most common industrial reverse auction format is the full price visibility format (Rangan 1998) in which bidders observe anonymous price bids and can respond in real time. Many industrial buyers tend to favor moving end-times (a “soft close”), meaning that any bid within the last minute of the designated closing time would automatically extend the close time by a few minutes to allow other bidders to respond.

Following the auction, the buyer may take 4-6 weeks to evaluate the individual bids and select a winner. During this time the buyer considers non-price attributes of interest and may review the bids with other functional units in its organization. Then all suppliers are notified as to whether they had won or lost the auction.

Given this approach to winner selection, it would seem that typical bidding strategies identified in the literature on forward auctions (such as outbidding the opponent as long as one’s reservation price has not been reached (McAfee & McMillan 1987)) may not be appropriate in this context. Being the lowest or second lowest bidder does not guarantee success and in fact, may cause the supplier to unnecessarily lose profit margin. Since suppliers do not know the identities of their competitors, they can only infer quality based on the bids that they observe

\(^2\) As an example, out of 13 lots for which we know the outcome, 4 winners had the lowest bid, and 6 winners had the second lowest bid; 3 winners were not the first or second lowest.
over the course of the auction. Our goal in the next section is to model how suppliers infer others’ qualities from their bids.

3. Model: A Model of Price Information Use

How do bidders respond to information from observed bids by others? Ariely & Simonson (1993) suggest that consumers’ general difficulty of assessing the value of goods and services in combination with the dynamic nature of decision-making in an auction can lead to an escalation of commitment to winning and consequent overpayment. This is because the subjective value of winning the auction increases when a consumer perceives others to be competitive for the same item (Heyman, Orhun & Ariely 2004). Ku, Malhotra & Munighan (2005) find that bidders get caught up in the “competitive arousal” of an auction, which leads to overbidding. While behavioral explanations are increasingly accepted in consumer auctions, the literature on business-to-business auctions has for the most part neglected individual level measures of bidding behavior. However, with the plethora of point-by-point bid data from online reverse auctions, the opportunity to better understand individual behavior is created.

In English auction settings, there is generally a weakly dominant strategy of outbidding competitors at each point in time by the minimum increment, as long as the net value of winning is positive to the bidder\(^3\). For example, if the bidding increment is $1000, a bidder should counter an opponent’s bid by bidding $1000 lower than the opponent. Regardless of one’s bidding strategy, a bidder should never let the auction expire at a winning price below his valuation and

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\(^3\) The dominant strategy described here is the same for forward or reverse, private, affiliated and common value auctions, but not for situations where sniping is possible. Since the present data has a soft ending time, sniping is not an issue.
should never enter a bid that is more than the minimum increment above the present highest bid\(^4\) (McAfee & McMillan 1987). Even though this prediction is not always observed, it can serve as a useful benchmark model.

Not so in buyer-determined auctions, where the buyer chooses the winner based on quality as well as price. Since bidders know their own quality and will not overly discount their bid (i.e., high quality bidders will not bid as low as low quality bidders), each bidder’s bids may reveal something about his quality—i.e., higher bids may be indicative of higher costs and might signal that the bid comes from a high quality bidder -- and therefore affect each bidder’s assessment of his own ranking on quality. Hence, the bidding behavior should depend on an inference about one’s chances of winning based on others’ bids. Though bidders do not know the other bidders’ attributes, they can nevertheless adjust their beliefs about others in response to past bidding behavior. This adjustment and response to competitive bidding represents a significant departure from the extant literature, which uses simplifying assumptions about perfect observability of quality attributes; i.e., new bids reveal no new information about bidders (Asker and Cantillon, 2008; Chen-Ritzo at al., 2005). In a online auction context, quality of others is not directly observed, nor can we assume it to be observed. Hence, we propose a model that would allow bidders to infer others’ qualities based on their bids.

In behavioral economics, a dominant theory is the theory of hierarchical thinking (Stahl and Wilson, 1994; Camerer, Ho and Chong 2004), which posits that human decision makers use iterative self-referential models of others. As a simple example (Bosch- Domènech et al., 2002), consider the following task. You must choose a number between 0-100. You will win a prize if your number is closest to 2/3 of the average choice by others like you faced with the same task.

\(^4\) Note that this definition of the set of weakly dominant strategies does not change in response to observed bids. That is, if the winning bid was 30 instead of 21, the set of dominant strategies would still be defined this way.
What will you choose? A naïve player might guess that since the possible range of numbers is from 0 to 100, the average will be in the middle of this range, at 50. In that case, the best choice is 33.3, which is 2/3 of the middle. One iteration on this idea—thinking that others are naïvely choosing 33.3—will result in a choice of 22.2. It turns out that empirically (in classroom, laboratory and newspaper experiments) the largest modes are indeed at 33 and 22 and that these modes are robust (in location though not in magnitude) (Bosch-Domènech et al., 2002).

In our setting, this suggests that bidders consider past bids and respond in one of two ways: (1) Naïve bidders try to outbid the minimum bid after adjusting for own quality. (2) Sophisticated bidders update their assessments of others according to how far others’ bids are from the minimum observed bid; they then try to outbid the minimum of quality-adjusted bids.

The classification of behavior into hierarchies of bounded rationality has been shown useful in different economic settings (Stahl and Wilson, 1994, 1995; Haruvy, Stahl and Wilson, 2001). Gneezy (2006), using the framework of Camerer, Ho and Chong (2004), applied a hierarchical classification to bidding in auctions. Whereas Gneezy restricted his attention to sealed bid forward auctions (in which bidders submit a single bid), in this work we apply a hierarchical theory to dynamic reverse auctions (in which bids are updated over time).

In an online reverse auction context, we can likewise model the two largest types of hierarchical thinking, which we call naïve and sophisticated. The naïve belief reflects an “insufficient prior,” and is defined as the belief that others possess identical qualities. We let that belief be an unbiased estimate of the true mean quality, meaning that the belief is correct on average. We define a “sophisticated belief” as the belief that all bidders other than oneself hold the beliefs that others hold insufficient priors. Then, we can state the following:
Proposition. A bidder with an insufficient prior will bid incrementally below the last observed minimum bid, adjusted for own quality. A bidder with a sophisticated belief will bid incrementally below the last observed quality-adjusted bid by others, adjusted for own quality.

All proofs are in the appendix.

4. Hypotheses

Our first hypothesis tests the basic premise of the model that the population consists of naïve bidders and boundedly rational sophisticated bidders. This hypothesis is consistent with the large stream of literature on hierarchical thinking reviewed earlier (see overview in Camerer, Ho, and Chong 2004) and with the finding that hierarchical rationality is consistent with auction data (Gneezy 2006).

Hypothesis 1. The population of bidders is a mixture of naïve and sophisticated bidders.

The buyer’s goal is to generate a surplus and competitive bidding. The next two hypotheses relate these outcomes to the correlation of bidder costs and qualities. Consider the case of positive and negative cost-quality relationships. A positive cost-quality relationship is likely when higher quality involves costly materials or operations (Asker and Cantillon, 2008). For example, more quality control generally increases both the cost and quality of a product. Negative cost-quality relationships occur when specialization is important in production (Smith, 1776). To this end, a number of large diversified firms such as IBM, Hewlett Packard, General
Motors and Motorola have sold off non-core operations in an effort to simultaneously improve quality and reduce costs (Burrow, 2005; Musgrove, 2004; Reardon, 2008; Welch et al., 2005).

We propose that competitive bid prices for a naïve population will be lower than prices for a sophisticated population when quality is highly positively correlated with costs and vice versa when quality is highly negatively correlated with costs. The rationale is that with sufficient positive correlation, the high quality bidders are also the high cost bidders and will be priced out of the auction before the lower quality bidders. Hence, the competition late in the auction will be between low-quality low-cost bidders. If the low quality bidders are sophisticated, they are aware that they are competing against other low-quality bidders, and they will therefore realize that they do not need to provide deep price discounts to remain competitive. However, if the low quality bidders are naïve, they will continue to provide deep discounts, to the great benefit of the buyer. In contrast, if there is a highly negative relationship between quality and cost, low quality sellers will be priced out first, leaving the high quality low cost sellers to compete later in the auction. In that case, the naive high quality low cost sellers will over-estimate their quality advantage vis-à-vis their surviving opponents, so bids will be higher than optimal in a naïve population, to the buyer’s detriment.

**Hypothesis 2.** The lowest bid in a naïve bidder population is lower than the lowest bid in a sophisticated bidder population when quality and costs are sufficiently positively correlated. The highest bid in a naïve bidder population is higher than the highest bid in a sophisticated bidder population when quality and costs are sufficiently negatively correlated.
The next hypothesis is the natural extension of the price comparison in the last hypothesis to buyer surplus. As long as the winner is the same winner in both populations, lower prices will translate into higher surplus for the buyer, where buyer surplus is defined as the highest score in the auction. Of course, this is not a direct mapping in the buyer-determined case, since it is often the case that the winners are not the same for both populations. However, if the relationship is sufficiently strong so that the set of bidders that are priced out is close in both populations, the savings on price will be the key difference. That is, when the cost-quality relationship is positive, buyer surplus will be higher for a population of naive types than for a population of sophisticated types and vice versa when the relationship is negative. Formally:

**Hypothesis 3.** The buyer surplus in a naïve bidder population is greater than the buyer surplus in a sophisticated bidder population when quality and costs are positively correlated and vice versa when they are negatively correlated.

This hypothesis need not imply a symmetric direction. Naive sellers, by virtue of behaving sub-optimally will typically yield additional surplus to the buyer over rational maximizing bidders. The buyer under most circumstances would prefer sellers to optimize poorly. The relationship between cost and quality should be quite negative before the buyer realizes significant benefit to rational bidders, and even then the benefit is expected to be quite limited. Also note that this hypothesis directly extends to the comparison of partial and full price information formats, as discussed in the previous section.

Note that the arguments with regard to positive cost-quality correlation apply only to populations with sufficiently large number of bidders. This is because the arguments rely on high-cost-high-quality bidders dropping out before the completion of the auction due to a
competitive process that eliminates them on cost-competitiveness. However, when there are few bidders and costs and qualities are drawn randomly, this argument may not hold. That is, when there are few bidders then with a high likelihood there will be cases where all bidders are high-cost-high-quality bidders. In these cases, naive bidders will bid too high relative to sophisticated, so sophisticated bidders would be strongly preferred in such cases. This leads us to hypotheses 4 and 5.

**Hypothesis 4.** The lowest bid in a naïve bidder population is greater than the lowest bid in a sophisticated bidder population when the number of bidders is sufficiently low regardless of correlation.

**Hypothesis 5.** The buyer surplus in a naïve bidder population is lower than the buyer surplus in a sophisticated bidder population when the number of bidders is sufficiently low regardless of correlation.

5. **Empirical Investigation**

In this section, we examine the hypotheses via proprietary data from two auction events and a simulation. The event data is used to test H1 (5.1-5.3) and simulations provide insights on H2 through H5 (5.4).

It is important to stress that the data does not include costs or qualities for each supplier, nor surplus for the buyer. Therefore, hypotheses 2 and 3 regarding cost-quality relationships cannot be reliably tested with the data, although the data is useful in calibrating the model for
subsequent simulation studies which we describe shortly. Likewise, due to the absence of buyer surplus information we cannot make conclusive statements about hypothesis 5 without a simulation approach. Hypothesis 4 includes variables for which we do have reliable measures (price, number of bidders, and bidder sophistication) but we simply do not have a sufficient number of independent auctions with different number of suppliers to be able to have reliable estimates. The simulation is helpful in that it can take parameters estimated from bid data, for which we have numerous observations, and use them to calibrate a simulation model which can then provide as many observations as we would like about hypothetical scenarios.

5.1. The Data

An industrial buyer in the automotive industry provided point-by-point bid data of ten online reverse auction lots held for two events-- metal parts and plastics. The combined contract value of these auctions was approximately $19.2 million. None of these products were pure commodities, such as MRO supplies or highly customized strategic parts. All the products were used in production or directly for parts in production. The product categories thus differed in non-price characteristics, and supplier relationships and quality could play a role in the procurement decision. The auction for metal parts consisted of 6 product lots and 20 bidders, while the plastics auction was comprised of 9 lots and involved 12 bidders. The lots are bid on simultaneously with bidders that overlap within each lot, but not across the two auction events. Since some of the lots have few or no multiple bids by the same firms, we cannot use these lots for estimation of dynamic updating. Deleting these lots, we are left with five lots in plastics and

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5 Incumbency is one potential measure of quality. We find that incumbency is negatively correlated with both the number of bids made in an auction and the concession made between the starting price and the ending price by the bidder. These could be indications that the incumbent faces a higher cost, or alternatively that the incumbent is sufficiently confident about its quality that it does not need to respond to others’ bids.
five lots in metal parts, for a total of 10 lots, or 472 bid observations. Summary statistics are given in Table 1.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std Dev</th>
<th>Min</th>
<th>Max</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Bidding Behavior</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. Supplier Bids</td>
<td>9.27</td>
<td>12.86</td>
<td>0</td>
<td>54</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. Bid Rate</td>
<td>0.15</td>
<td>0.20</td>
<td>0</td>
<td>0.74</td>
<td>0.77 1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. Price Concessions</td>
<td>0.15</td>
<td>0.17</td>
<td>0</td>
<td>0.58</td>
<td>0.76 0.66 1.0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. Auction Duration (in minutes)</td>
<td>63.35</td>
<td>38.52</td>
<td>6</td>
<td>213</td>
<td>0.43 -0.07 0.32 1.0</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Correlations greater than .26 are significant at p = .05

The first three summary statistics are indicative of bidder aggressiveness: (1) the average number of bids entered by a supplier, (2) bidding rate—the average number of bids entered by a supplier divided by duration of the auction event, and (3) price concession—the average price drop by a supplier from its first to its last bid. These three variables are highly correlated, supporting the claim that they loosely correspond to the same construct. Lastly, we report average event duration in minutes. Absent from this summary is the number of bidders, which we elaborate on shortly.

5.2. Auction Rules

The purchase contract is broken into lots or sub-groups of multiple items typically organized according to the suppliers’ capabilities to bid on or produce each lot, similarities in manufacturing processes, delivery regions, etc.

The auctions begin with the buyer issuing a request for purchase that details the nature of the contract as well as product, delivery, and handling specifications and expectations. Then, a set of pre-qualified suppliers are invited to bid in an online auction for the potential opportunity.
to win the purchase contract. The auctions are “buyer-determined” score auctions, allowing buyers to integrate non-price considerations (e.g., quality and reliability) into their selection decision. The score is defined as

\[
\text{Score(bidder } j) = \text{Monetary Quality measure for bidder } j - \text{bid by bidder } j
\]  

(1)

The bidder with the highest score wins, rather than the bidder with the lowest price. In contrast to score auctions with endogenously determined qualities, however, in the present auctions, the bidders bid on price only. Their qualities, as far as the auction goes, are exogenous.

Quality determination occurs both before the start of the auction and after the conclusion of the bidding. Prior to the auction, bidders are pre-qualified to ensure that they meet the minimum quality standards. In addition, the minimum measurable product quality and technical specifications are provided to the bidders in detail and it is made clear that the products must meet these specifications. Following the conclusion of the bidding, the buyer takes several weeks to evaluate the bids based on any number of criteria, including past relationships with the supplier, reputation for service, etc. Visits to the bidding firm to inspect the manufacturing process and quality control are common.

All the auctions were conducted by a third party auctioneer who informed the suppliers of the event rules. The suppliers were not told who their competitors were or how many suppliers would bid against them and featured a soft close.

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7 It is important to note that though the auction itself may not determine the winner, a buyer-determined auction nevertheless plays a critical role in the buyer’s price discovery efforts and supplier choice. Instead of thinking of each bidder as submitting a price, one could think of each bidder as submitting a score involving a price + non-price attributes. The winner is not the lowest bidder, but the one that presumably scores the highest on both price and non-price characteristics. To this end, the theoretical treatment of this price discovery mechanism is equivalent in all respects to that of auctions in which the lowest bidder wins.
The average number of active bidders was 7.1. The distribution of the number of bidders in our auctions is given below.

**Figure 1. The distribution of the number of bidders over lots.**

![Graph showing the distribution of the number of bidders over lots.]

5.3. *Estimation Methodology*

As mentioned earlier, heterogeneity in bidder sophistication is a critical aspect of the current estimation methodology and the normative predictions of the model. Heterogeneity considerations have been shown to be critical in the design of auctions (Bapna, Goes, Gupta and Jin, 2004). We utilize a mixture model to assess the degree of hierarchical thinking among the bidders. The mixture model contains two types of bidders: naïve and sophisticated. The proportion of each segment in the population is denoted by $a_j$, where $j$ is the corresponding segment.

Denote by $\text{bid}_{it}$ the last observed bid by firm $i$ at or before time $t$ and let the variable $\text{diff}^{0}_{it}$ denote the bidder’s demanded premium over the unadjusted last minimum observed bid by others. The variable $\text{diff}^{+}_{it}$ denotes the bidder’s demanded premium over the last minimum
observed bid by others, adjusted for others’ quality advantages or disadvantages inferred from their bids.

The adjustment rate is denoted by parameter $\beta$, which represents the degree of adjustment of firms’ beliefs about the qualities of other firms. If $\beta=1$, firms fully adjust their belief regarding others’ qualities in response to the last observed bid. That is, each sophisticated firm believes that firm k’s quality advantage is fully reflected by its last observed bid. If $\beta=0$, firms never update their initial belief (which would mean that sophisticated firms are essentially naive). For any intermediate $\beta$, the new belief is equal to a convex combination of the previous belief and the last observation, with a weight of $(1-\beta)$ on the previous belief and a weight of $\beta$ on the last observed bid. Note that the belief regarding firm k is only updated when a new bid is observed by firm k.

Since $diff_{it}^0$ and $diff_{it}^1$ need to be initialized, we initialize them at the first observed difference and drop the first observation from estimation.

\[
\min_{t-1}^0 = \min(bid_{1,t-1}, \ldots, bid_{n,t-1})
\]  

(2)

\[
diff_{it}^0 = (1-\beta)diff_{it-1}^0 + \beta(bid_{it} - \min_{t-1}^0)
\]  

(3)

\[
\min_{t-1}^1 = \min(bid_{1,t-1} - diff_{1,t-1}^0, \ldots, bid_{n,t-1} - diff_{n,t-1}^0)
\]  

(4)

\[
diff_{it}^1 = (1-\beta)diff_{it-1}^1 + \beta(bid_{it} - \min_{t-1}^1)
\]  

(5)

Since some buyers bid on several lots within an event, we need to account for potential correlation. To do that we use the random effects model to allow for a common error term, $\varepsilon_i$, to enter for bids by the same firm across lots. The error term $\varepsilon_i$ is assumed to come from a
normal distribution with mean zero and standard deviation $\sigma_{ind}$. The likelihood over firm i’s bids conditional on firm i being naïve (Type 0 in equations 6 and 7) or sophisticated (Type 1 in equations 6 and 7) is:

$$L_i\text{(Type } j) = \prod_{t=1}^{T} \frac{1}{\sigma_{lot}} \phi\left( \frac{bid_{i,t} - \min_{j=0,1}^{T} diff_{i,t}^{j} + \varepsilon_{i}}{\sigma_{lot}} \right)$$

(6)

The unconditional likelihood of firm i’s bids is:

$$L_i = \sum_{j=\{0,1\}} \alpha_j L_i\text{(Type } j)$$

(7)

The parameter $\alpha_1$ denotes the proportion of sophisticated firms.

This gives us a model with two main parameters $\alpha_1$ and $\beta$. We also need a parameter for the standard deviation of error for each lot and one parameter for the standard deviation of individual random effects. Though we assume the same $\alpha_1$ and $\beta$ over lots, the scale is different between lots, requiring a separate sigma (variance parameter) for each lot. Model estimation is detailed in the next section (§5.3).

5.3. Estimation Results

The estimation was run in Gauss, and an optimization procedure (OPTMUM) was used for maximization. We estimated three models—the homogeneous naive model, the homogenous sophisticated model, and a mixture model that allows for both types of bidders as subpopulations in the bidder population. Table 2 shows the parameter estimates and their significance for the mixture model only; we use the likelihoods from the homogenous models for hypothesis testing.

Table 2 Results for all events pooled

Coefficient $\alpha_1$ denotes the proportion of sophisticated bidders; $\beta$ is the degree of adjustment of firms’ beliefs about the qualities of other firms. $\sigma_1$, $\sigma_{10}$ and $\sigma_{ind}$ are
random effects; $\sigma_1 - \sigma_{10}$ denote the standard deviation for lot-specific effects. $\sigma_{ind}$ denotes the standard deviation for individual bidder specific effects.

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Estimate</th>
<th>t-stat</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta$</td>
<td>0.646</td>
<td>20.05</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>$\alpha_1$</td>
<td>0.378</td>
<td>5.094</td>
<td>0.001</td>
</tr>
<tr>
<td>$\sigma_1$</td>
<td>0.029</td>
<td>15.324</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>$\sigma_2$</td>
<td>0.029</td>
<td>9.455</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>$\sigma_3$</td>
<td>0.01</td>
<td>26.51</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>$\sigma_4$</td>
<td>0.021</td>
<td>25.366</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>$\sigma_5$</td>
<td>0.013</td>
<td>13.403</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>$\sigma_6$</td>
<td>0.037</td>
<td>24.342</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>$\sigma_7$</td>
<td>0.042</td>
<td>42.659</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>$\sigma_8$</td>
<td>0.025</td>
<td>44.289</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>$\sigma_9$</td>
<td>0.06</td>
<td>29.84</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>$\sigma_{10}$</td>
<td>0.062</td>
<td>15.67</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>$\sigma_{ind}$</td>
<td>0.004</td>
<td>2.93</td>
<td>0.004</td>
</tr>
</tbody>
</table>

The homogenous naive model is nested in the mixture model, with $\alpha_1$ restricted to zero. It yields a log-likelihood of 789.0, which, by the likelihood ratio test, is significantly worse at the 1% level of significance. The homogenous sophisticated model yields a log-likelihood of 780.1. Nested in the mixture model, with $\alpha_1$ restricted to zero, it too can be rejected at the 1% significance level. Hence, we can say that the homogenous models can be rejected in favor of a mixture model, supporting hypothesis 1. The above results demonstrate that roughly 40% of the participants incorporate information about others’ bids into their own bids.

Note that we have not used available data about public and private measures of own quality from each supplier, including objective measures like incumbency and certification as well as subjective measures such as relationship assessment. The variable $diff^0_t$ fully captures the intrinsic quality premium of a firm in an auction and the random effects error term captures
remaining firm-specific effects, leaving no room for additional firm level regressors to improve the fit.\textsuperscript{8} Hence, we will have to conduct a separate analysis for these individual firm variables using a somewhat different framework.

### 5.4. Simulation Results

The current data does not allow for good estimates of bidder costs or consideration of the implications for auction format selection. First, these estimates would be inseparable from any error in the estimate of the quality for each bidder. Second, since bidders enter at random times, we do not have perfect observability of when the bidder exits, which would be necessary to pinpoint its cost. We could make various assumptions and get some numbers, but these numbers would not be very meaningful. Moreover, we would like to ask “what if” questions about the relationship between cost and quality and the impact of the number of bidders.

To understand how the relationship between cost and quality affects buyer surplus and the choice of optimal auction format, we simulate bidders with different costs and qualities. The bidders come from one of two bidder populations (i.e., naïve and sophisticated) that together make up the mixture observed in the data. Instead of looking only at the mixed population, we examine each population type separately. This is because each population type represents a mode of behavior we expect to see prevalent in one either the full or partial price visibility formats. Under the partial price visibility format, the only bidding strategy possible is one corresponding to the behavior of a naive population, whereas under the full-visibility format, more sophisticated strategies are possible, as demonstrated by a sophisticated population. It is therefore of interest to separately compare these two extreme cases of pure populations.

\textsuperscript{8} With individual effects terms, additional demographic variables, unless they vary over time, cannot add to fit or be identified since all the heterogeneity in the intercept is already captured.
The parameters of the simulation are as follows. We simulate 2 to 20 bidders for each of the 10 auction lots with cost-quality covariance parameter of -30 to 30 (correlation is covariance divided by the product of the standard deviations). For each lot, we begin with an average initial bid that is the initial bid we observed in the actual data. The quality differential of each bidder is randomly determined and uniformly distributed between \(-0.4*\tilde{b}_0\) and \(0.4*\tilde{b}_0\). The cost is related to the quality differential through \(c_i = \gamma\text{diff}_i\) where \(\gamma\) determines the sign and strength of the relationship between cost and quality differential and is the parameter we vary to study the effect of this relationship on buyer surplus. Another stochastic element of the simulation is in the incidence and timing of each bidder’s bid (which of course, affects the bid amount). Each bidder bids probabilistically at each point in time, with a probability of 1/10.

Figure 2 shows the difference in lowest observed price between an auction taking place in a population of naive bidders and an auction taking place in a population of sophisticated bidders for 2 to 20 bidders and cost-quality covariance of -30 to 30. Whereas the left-hand side depicts the simulation over varying numbers of bidders, the right hand side of Figure 2 simplifies this effect by showing a sliver of the overall simulation for 8 bidders only.

**Figure 2 Price Difference plotted on the number of bidders and covariance (left) and on covariance only with the number of bidders fixed at 8 (right)**
We see from Figure 2 that for any given number of bidders, there is a cutoff covariance for which the naive population’s price drops below the sophisticated population’s price. We see on the right hand side that for 8 bidders that cutoff is at a covariance of 0. That is, for 8 bidders, a positive correlation between cost and quality implies that the price would be higher with a sophisticated population.

Figure 3 shows the parallel difference in buyer surplus, where buyer surplus is defined as the highest score, as defined by equation 1. Recall that the difference between score and price is that score takes quality, or buyer preference into account. Ideally, the buyer would like to contract with the highest score bidder rather than the lowest price bidder. In other words, the appropriate objective function for the buyer is buyer surplus which is the highest score. The right hand side of figure 3 shows a sliver of the overall simulation in two-dimensions for 8 bidders only.

**Figure 3 Surplus difference plotted on the number of bidders and covariance (left) and on covariance only with the number of bidders fixed at 8 (right)**

The more meaningful comparisons for cost-quality correlation occur between 7 and 9 bidders. For under 7 bidders and over 9 bidders, the cost-quality correlation is not a critical variable for the choice between formats; the key variable for consideration is the number of bidders. The graphs for 8 bidders, which represent 7 and 9 bidders as well, where half of our...
observations fall, clearly show that when the cost-quality relationship is strongly positive, lower price would be observed in a naive population of bidders than in a sophisticated bidder population. This provides insight into hypothesis 2 in the positive relationship case. The opposite holds for the negative cost-quality relationship scenario. In terms of surplus, when the cost-quality relationship is positive, the buyer would obtain greater surplus with a naive population than a sophisticated population, or alternatively pursue a partial price information auction format rather than a full price information format. When the relationship is strongly negative, the buyer would slightly prefer a sophisticated population or a full price information format. This speaks to hypothesis 3.

Note that when the cost-quality relationship is negative, the price and score differences between the populations/formats are largely negligible for 9 or more bidders, though they are substantial for 8 bidders or less. In other words, the optimal choice of populations/formats does not yield symmetric benefits. Choosing the partial price information auction format when it is the optimal format could yield tremendous benefits over a full-price-information format. But choosing it when it is not optimal will not cause great, if any, losses to the buyer provided the number of bidders is sufficiently large. This is not an artifact of the parameters chosen for the simulation. Rather, it is a robust characteristic of this setting. To understand this, note that the critical statistic in a naive population is the minimum price bid. In the positive relationship scenario, the buyer surplus advantage of a naive population over a sophisticated population stems from low quality bidders over-discounting their own qualities relative to their opponents, which results in jump bidding or bidding down in increments greater than the minimum increment. In contrast, in the negative cost-quality relationship scenario, the naive bidders are expected to bid higher than optimal because high quality naive bidders (the bidders whose low cost allows them
to continue bidding late into the game) will overestimate their quality advantage relative to their opponents. However, any bidding up will not affect the minimum price bid statistic which is the only information the naive evaluate. Hence, the effect is minimal. Mostly, what is happening is that prices decline by the minimum increment instead of by jump bids. But this is exactly the pattern in the sophisticated population. While the impact is therefore negligible on the prices, it is somewhat more significant for buyer surplus. In the calculation of buyer surplus, bids higher than the minimum matter and this is why surplus appears to be more affected than prices by the population makeup in the negative relationship scenario.

As predicted by hypotheses 4 and 5, when the number of bidders is small, the covariance, and therefore correlation, will not be a key determinant in population or format choice. Price will always be higher and buyer surplus will always be smaller for the naive population regardless of the correlation. This is because high-cost bidders are less likely to drop out of the auction. We find strong support for this notion, related to hypotheses 4 and 5.

In summary, when the buyer knows the cost-quality relationship and the number of bidders is sufficiently large, a positive cost-quality relationship implies an advantage for a partial price format or naive population and vice versa. When the number of bidders is sufficiently large and the buyer is uncertain about the cost-quality relationship, the buyer’s format choice is not difficult—the partial price information dominates easily. However, when the number of bidders is small this preference reverses and the optimal format choice becomes full price visibility.

6. Conclusions

We proposed that in procurement auction settings sellers’ bids should increase in their qualities. Accordingly, bidders should be able to infer others’ perceived quality advantage or
disadvantage and to re-assess their own relative standing. Since the equilibrium is intractable in such settings, we proposed a framework of hierarchical bounded rationality with two levels of sophistication.

We examined the assertion that sellers infer others’ qualities from their bids using data from ten auction lots. We found that a little over 60% of suppliers were naïve bidders in that they did not appear to derive information from others’ bids. Almost 40% of participants could be said to have sophistication in that they attempted to infer others’ qualities from their bids. While others (Gneezy, 2006) have suggested a hierarchical mixture approach to bidding, this is the first demonstration that the hierarchical mixture approach can be successfully applied to dynamic reverse auctions.

From the buyer’s perspective, we showed that when the number of bidders is sufficiently large, a buyer would prefer to be facing a naïve population of bidders when the relationship between cost and quality is positive, but would prefer to face a more sophisticated bidder population when the cost-quality relationship is negative. When the number of bidders is small, however, the buyer would prefer to face a sophisticated population. While a buyer may not always have a choice of which bidder population to face, the buyer typically has a choice of which auction format to use. In partial price visibility formats, sellers are essentially reduced to naive behavior as they have no ability to assess other bidders’ qualities. Hence, the comparison between naive and sophisticated populations directly pertains to the comparisons between partial and full price visibility formats. We can conclude that when the expected number of bidders is sufficiently large, a buyer would prefer a full price visibility format to the partial price visibility format when the cost-quality relationship is negative and vice versa. When the expected number of bidders is small, the full visibility is preferred regardless of the cost-quality relationship. This
is an important characterization to sellers facing this critical format choice. This result appears to be in contrast to findings elsewhere (e.g., Goeree and Offerman, 2003) that more information provided by the auctioneer reduces uncertainty and thereby promotes more aggressive bidding. The difference is that the bidders in our model are boundedly rational and map information in ways that are not in accordance with full rationality.

Limitations

Since the findings of the paper are simulation-based, the data simply served as a benchmark calibration of the model and presented some limited evidence for the model’s predictive power. Nevertheless, while this data set is novel and informative, it is not necessarily ideal. The main limitation of the present study is that the data did not contain the actual qualities and costs of the bidders. Instead, they had to be estimated under the assumptions of the model, which could lead to misspecification-related biases.

Another approach for examining alternative levels of bidder sophistication would be to use experimental data in which the qualities and costs are known. However, this approach is not without tradeoffs. Even under such conditions, it can still be quite difficult to decipher and isolate alternative levels of sophistication. This is the what Gneezy (2005) finds. In addition, external validity might also be sacrificed.

Managerial Implications

With the popularity of procurement auctions fast rising, numerous new formats have been proposed. Most of these formats have been devised to satisfy buyer and seller needs and requests
with little regard for the theoretical tractability of such formats for economists, leaving a large vacuum in the academic auction literature.

In this work we examined the surplus implications for the buyer of truncating price information. We noted that price truncation would lead to less aggressive responses to high quality bidders’ bids and to more aggressive responses to low quality bidders’ bids. Hence, the surplus difference of truncating prices could go either way.

With few bidders, the surplus loss from less aggressive competition in a group of high quality bidders far outweighs the surplus gain in a group of low quality or mixed quality bidders since the high quality bidders have a greater surplus potential. Hence, with small groups, the buyer should opt for full price visibility. Larger groups of bidders are likely to consist of the full quality spectrum and in these auctions the low quality bidders drive the price down for the high quality bidders. Hence, for larger numbers of bidders the buyer should opt for a partial price visibility format.

The cost-quality relationship is equally important for the price visibility decision. With partial price visibility, low quality bidders are the ones that drive prices down relative to full price bidding, whereas high quality bidders drive prices up. With a positive cost-quality relationship, low quality bidders are also low-cost and therefore can drive prices down more. With negative cost-quality relationship, low quality bidders are high-cost and are priced out of the market early in the bidding. Hence, in the positive cost-quality relationship, the buyer would opt for price truncation where with a negative cost-quality relationship, full price visibility would be preferred.

While our framework is useful for the buyer’s decision on price visibility in online reverse auctions, it is also useful for the seller’s bid decision. From a seller’s perspective,
knowing where your company stands relative to others is invaluable information to managers. Any statistical method which can help infer others’ qualities would be tremendously helpful to formulate a bidding strategy. No less important is knowing how the competition might use one’s bids to infer information about one’s competitive position and bidding strategy. Both of these issues were addressed by our empirical model and we believe they will prove important to managers.

**Future Research**

Future research should sort out various dynamic bidding strategies. With more and cleaner data, one might be able to identify higher levels in the sophistication hierarchy as well as dynamic strategies such as signaling and collusion.

In the limitations section, we mentioned the potential ability of experimental research to cleanly estimate and test the explanatory power of the present model and alternative models. However, the most promising experimental route for this line of research, in our opinion, would be to examine the implications of the price truncation policy offered here, rather than to try to confirm one model or another.

In this work we examined partial versus full price visibility. Another increasingly popular format is the rank-based format which can be studied in the present framework. The rank-based format, where bidders are informed of their rank relative to others but not of any competing price offers, can be thought of as a hybrid between full and partial price visibility and we expect results in-between the two formats we already studied.

The attributes we focused on were the degree of correlation between cost and quality and the number of bidders. Another related attribute which could be studied in the present format is
the variance in bidder quality. Together, these possibilities present exciting avenues for future research.
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APPENDIX

Proof to Proposition: To win the auction, a naive bidder $i$ would simply need to beat the score of the highest score opponent. Given the belief that all others possess a quality of $\bar{q}$, this highest score by an opponent is $\max_{j\neq i}(q_j - bid_{j,t-1}) = \bar{q} - \min_{j\neq i}(bid_{j,t-1})$. To beat that score, it must be that $(q_i - bid_{i,t}) = \bar{q} - \min_{j\neq i}(bid_{j,t-1}) + \epsilon$, which is $bid_{i,t} = \min_{j\neq i}(bid_{j,t-1}) + q_{diff} - \epsilon$.

Sophisticated bidders believe other bidders are naive. If one believes that others are naive, then he believes that their bids reveal their qualities perfectly. Hence, the auction becomes a regular reverse English auction in the score space.

To win, bidder $i$ needs to bid such that

$$(q_i - bid_{i,t}) > \max_{j\neq i}(q_j - bid_{j,t-1})$$

Or

$$bid_{i,t} < \min_{j\neq i}(q_i - q_j + bid_{j,t-1})$$

By definition, $q_i = q_{diff} + \bar{q}$ and $E_i^0(q_i) = E_i^0(q_{diff}) + \bar{q}$, so

$$bid_{i,t} < \min_{j\neq i}(-E_i^0(q_{diff}) + q_{diff} + bid_{j,t-1})$$

Or

$$bid_{i,t} - q_{diff} = \min_{j\neq i}(bid_{j,t-1} - E_i^0(q_{diff})) - \epsilon$$