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DESIGN AND EVALUATION OF FEEDBACK SCHEMES FOR MULTIATTRIBUTE PROCUREMENT AUCTIONS

Conception et évaluation de systèmes de rétroaction pour des enchères d'achat multi-attributs

Completed Research Paper

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Abstract

Multiattribute auctions, which allow bids on multiple dimensions of the product, are IT-enabled sourcing mechanisms that increase the efficiency of procurement for configurable goods and services compared to price-only auctions. Given the strategic nature of procurement auctions, the amount of information concerning the buyer's preferences that is disclosed to the suppliers has implications on the profits of the buyer and suppliers and, consequently, on the long-term relationship between them. This study develops novel feedback schemes for multiattribute auctions that protect buyer's preference information from the supplier and suppliers' cost schedule from the buyer. We conduct a laboratory experiment to study bidder behavior and profit implications under three different feedback regimes. Our results indicate that bidders are able to extract more profit with more information regarding the state of the auction in terms of provisional allocation and prices. Furthermore, bidding behavior is substantially influenced by the nature and type of feedback.

Keywords: Procurement auctions, multiattribute auctions, information feedback, bidder behavior, experimental economics.

Résumé

Cette étude développe de nouveaux systèmes de rétroaction pour des enchères multi-attributs qui assurent à l'acquéreur la confidentialité de l'information sur ses préférences et qui garantissent à l'offreur la confidentialité de l'information sur ses coûts. Une expérimentation est menée pour étudier le comportement et les gains de l'offreur dans le cadre de trois types différents de rétroaction.

Introduction

Industrial procurement is an important part of the supplier selection problem, which is concerned with the selection of vendors followed by the determination of the nature of contracts with them. With the rapid advances in information technology (IT), auctions are being increasingly used for the procurement of goods and services. Procurement auctions enable multiple suppliers of goods and services to competitively bid for the business of a single customer or buyer. The process involves identifying, evaluating, negotiating, and configuring optimal sets of suppliers' bids, which are usually received in response to the procuring firm's request for quote (RFQ). The objective is primarily to minimize the total procurement cost subject to various business constraints. The complexity of the process depends on the quantity of items procured, number of participating suppliers, and also the business constraints associated with it.

Corporate procurements often require a supplier to fulfill several required characteristics of a contract – both qualitative and quantitative – in addition to price. However, conventional auction mechanisms restrict the negotiations solely to price while keeping other elements of the contract fixed. Therefore, these auctions are not well suited for procurement problems where commodities require detailed technical specifications, because they compel buyers to commit to specific configurations of the product in advance. Ideally, buyers would like to negotiate all the dimensions of the contract simultaneously with all potential suppliers in order to create the best purchase agreement. With the flexibility afforded by the Internet and the computational power of new technologies, it is possible to design advanced mechanisms that take into account multiple facets of the contract and not just price.

Multiattribute auctions[1] represent such a mechanism, which extends the traditional auction setting by allowing bids over price as well as non-price attributes. In a procurement problem, a multiattribute auction can allow different suppliers to compete over qualitative attributes, such as supplier reputation, terms of warranty, and lead time, in addition to price. These auctions provide buyers the ability to negotiate over a multidimensional space of product characteristics. Prior research has shown that, multiattribute auctions can achieve higher market efficiency through better information exchange of buyer's preferences and suppliers' capabilities, compared to price-only auctions (Chen-Ritzo et al. 2005). Other expected gains include faster negotiation and higher market transparency. Many software vendors and procurement departments now support multiattribute reverse[2] auctions in their e-sourcing solutions. Such firms include Ariba, freemarkets, Procuri, and i2 technologies (Minahan et al. 2002).

While multiattribute auctions allow suppliers to better express their production capabilities, they also present a complex bidding environment where bidders have to solve difficult optimization problems to prepare efficient multidimensional bids. Therefore, in order to ensure that the environment is sufficiently easy to use for bidders, it is necessary to design appropriate feedback mechanisms that can assist bidders in preparing their bids. However, considering that procurement is a key source of strategic advantage for many organizations, the amount of information the buyer should disclose or try to elicit from the supplier is a critical and sensitive issue. A buyer may not want to reveal her complete preferences in order to foster more competition and drive down price while a supplier may not want to disclose his production schedule in order to maximize his profits. While a less transparent mechanism may benefit a buyer, it may also alienate prospective suppliers.

Thus, companies such as Ariba suggest that buyers employ a variety of information disclosure schemes for traditional procurement auctions based on the specific negotiation requirements and on the structure of the market for the commodity being procured. For example, if the auction is for a commodity that has few suppliers and is of

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[1] These have been variously referred to as multidimensional (Che 1993; Koppius et al. 2000), multiissue (Teich et al. 1999), and multicriteria (De Smet 2007) auctions in the literature.

[2] In reverse auctions, a buyer solicits bids from a group of potential sellers.

high strategic importance, then Ariba suggests using sealed-bid auctions, i.e., an auction format with no intermediate information revelation. On the other hand, if the auction is for a commodity with a large number of suppliers and of little strategic importance, then Ariba suggests using more transparent auctions, such as English and Dutch auctions. In many other cases, Ariba provides a variety of mechanisms with different restrictive feedback schemes that are somewhere between completely sealed and completely transparent[3].

In order to facilitate the use of multiattribute auctions for automated strategic sourcing processes, we have designed multi-level feedback schemes intended to foster competition and make the environment transparent while also protecting buyer's preferences and suppliers' cost schedule. The schemes consist of information regarding provisional allocation that can potentially make bidders better aware of the auction state, and price signals that are expected to assist bidders in revising their bids. Of interest is how each of these feedback schemes affects bidder behavior and the distribution of the economic surplus among the buyers and the suppliers. To study bidder behavior, we conduct a laboratory experiment, wherein subjects participate in hypothetical multiattribute procurement auctions. We find that the nature of feedback can significantly influence bidder behavior as well as the distribution of gains between the buyer and the suppliers. Our results indicate that, even with similar allocative efficiency, the buyer can control the extent of information disclosure to achieve specific auction objectives.

Literature Review

Procurement auctions come in a variety of forms depending on the structure of the market and the needs of the buyer. Elmaghraby (2000) provides a survey of the existing research on procurement auctions in the areas of economics and operations research, especially the research on the choice of a specific sourcing strategy. Multiattribute auctions are of special importance to procurement contexts since buyers are almost always interested in not just price but other aspects of the contract such as quality and delivery time.

Multiattribute auctions as models for procurement were first studied by Che (1993). He studied an auction protocol in which the negotiation was based on price as well as quality in a sealed-bid setting. He assumed that each seller was characterized by only one private cost parameter, which the buyer was assumed to know. Branco (1997) extended this model by introducing cost correlation among bidding firms. Furthermore, he used a two-stage auction, in which the procurer selected a firm in the first stage and then negotiated to readjust the quality level in the second. Both Che and Branco assumed that the buyer has perfect knowledge of the bidders' cost structures. However, our objective is to conduct auctions, where suppliers do not have to disclose their cost schedule to the buyer.

An approach often taken to evaluate multidimensional bids is to assign weights to the relevant attributes to compute a value score for the buyer[4]. The score is expected to reflect the utility derived by the buyer from the bid. Bidders can then compete to improve this score by modifying one or more of the bid-attributes. This approach is used by software vendors such as Epicor, IBM, Moai Technologies (Bichler and Kalagnanam 2005), by US highway procurement authorities (Herbsman et al. 1995), and in the auctions for electricity reserve supply (Wilson 2002). Asker and Cantillon (2008) show that scoring auctions dominate several other procedures (e.g., menu auctions[5], beauty contests[6], and price-only auctions) for buying differentiated products. We use such a scoring rule approach in our design of multiattrbute auctions. Bichler et al. (1999) used a utility-function approach to study some internet-based implementations of multiattribute procurement auctions. They outlined some theoretical questions associated with multiattribute auctions and also described an implementation of the mechanism. Beil and Wein (2003) considered iterative multiattribute auctions where the buyer changed his scoring rule during the auction based on bids in the previous rounds. However, in this paper we consider multiattribute auctions that are based on an explicit model of buyer's preferences.

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[3] Jason Solinger, "ARIBA Spend Management," Presentation at University of Minnesota, Nov. 19, 2007.

[4] Multiple Attribute Utility (MAU) theory addresses the issue of converting multiple performance measures to a scalar performance metric. For a thorough review of MAU, see Keeney and Raiffa (1976) and Winterfeld and Edwards (1986).

[5] In a *menu auction*, the suppliers submit menus of price and non-price attributes from which the buyer chooses the combination that best suits her needs.

[6] In a *beauty contest*, the buyer tells the suppliers that she cares about other attributes of the product in addition to its price but accepts a single bid from them, and chooses the bid he prefers from the received bids.

Bichler (2000) compared the efficiencies of multiattribute and price-only auctions through laboratory experiments and he found no significant difference. Strecker (2003) conducted two sets of English auction experiments with two qualitative attributes, where the buyer's scoring function was fully revealed in one of the auctions and not revealed at all in the other. He found full revelation to increase both allocative and Pareto efficiency of the auction. Similarly, in several experimental studies, Koppius and van Heck (2003) found that revealing more information about buyer's preferences improved the auction performance in terms of Pareto efficiency. However, according to Pinker et al. (2003), these results may not be practical, given that most firms seek to maximize their own utility rather than achieve economic efficiency for a market, and given that firms may also be reluctant to directly reveal their utility functions to competitors.

Therefore, with more practical auctions in mind, we study cases where the buyer does not reveal her entire scoring function but provides several other pieces of information that would help the bidders in their bid formulation. The impact of this kind of feedback has recently been experimentally studied by Chen-Ritzo et al. (2005). They found their restrictive feedback mechanism to increase both buyer utility and supplier profits compared to price-only mechanisms. However, the procurement auctions that they conduct are sole-sourcing, i.e., the contracts are awarded to a single supplier. Such restrictions are appropriate for goods with high asset-specificity (e.g., weapons systems procured by Department of Defense) and were imposed in early evaluations of multiattribute auctions for alleviating computational complexities. But with the increasing use of mutiattribute auctions for less specific assets (e.g., MRO procurement), multiple sourcing becomes more important (Bichler and Kalagnanam 2005). Furthermore, with the rapid advancements in IT, it is now feasible to conduct these auctions in real-time. In this paper, we evaluate several feedback schemes for multiple sourcing scenarios. We consider a situation where a buyer requires several units of an asset that she is willing to purchase from multiple suppliers.

Laboratory data forms an important means of analyzing and comparing complex auction mechanisms. It allows us to calculate performance measures under controlled conditions that are impossible in field studies. Numerous studies have shown that, even in simple price-only auctions, bidders behave differently from what the theory predicts (Coppinger et al. 1980; Holt 2007; Kagel et al. 1987). Thus, laboratory environments have been widely used as testbeds for auction designs, especially for complex mechanisms, such as multiunit auctions (Bapna et al. 2001), combinatorial auctions (Adomavicius et al. 2007; Banks et al. 1989; Kwasnica et al. 2005), and multiattribute auctions (Bichler 2000; Chen-Ritzo et al. 2005; Koppius and van Heck 2003; Strecker 2003).

In order to evaluate the effects of varying quality and quantity of feedback on bidder behavior in mutiattribute auctions, we conduct a laboratory experiment, where subjects play the role of suppliers competing to sell several units of an asset to a buyer. The buyer is designed as an automated agent, who evaluates bids based on a predefined utility function. Although we do not reveal this utility function to the suppliers because of the strategic reasons described earlier, we provide novel price signals to the bidders to help them revise their bids. In the next section, we describe our design of the multiattribute auction environment that allows us to conduct such auctions in the laboratory.

Multiattribute Auction Design

We simulate a multiattribute bidding scenario with m suppliers, a single buyer, and k identical units of a commodity, each defined by a quality attribute q in addition to its unit price p. The quality attribute has several discrete abstract levels, denoted by $q \in Q = \{0.00, 0.01, 0.02, ..., 1.00\}$. Our rationale for using an abstract range for quality is the observation that, in industrial procurement, companies usually specify an acceptable range of the quality of a product. For example, a company procuring floppy disks can specify that the acceptable range of the space between the read/write head and the disk is between 0.0 and 0.2 microns. In that case, quality level 0.01 can represent the maximum tolerance and quality level 1.00 the optimal space.

The buyer requires multiple units of the commodity, which she can choose to source from any number of suppliers (multiple sourcing); quantity $n \in N = \{1, \ldots, k\}$ is also negotiable along with the price and quality. In other words, bid b consists of a specification of quality level, price, and quantity; i.e., $b = (p, q, n)$.

We use a standard (see for example, Chen-Ritzo et al. 2005) non-linear valuation function for the buyer that monotonically increases in quality. This function is given by $v(q) = A_0 q^{\alpha_0}$, where $A_0 > 0$ and $0 \le \alpha_0 \le 1$ are quality-related constants for the buyer. We assume that the buyer prefers higher quality product (other things being equal) with a decreasing marginal value. The utility function of the buyer is derived from the valuation function by subtracting the weighted price of the commodity. The utility of a bid non-linearly increases with quantity because typically a buyer prefers to buy as many units from a supplier as possible in order to minimize the transaction cost of procurement. The utility function is thus:

$$U(p,q,n) = \left(A_0 q^{\alpha_0} - Bp^{\beta}\right)Cn^{\gamma},$$

where $B > 0$ and $0 \le \beta \le 1$ are price-related constants, and $C > 0$ and $\gamma \ge 1$ (since the marginal value of quantity is increasing) are quantity-related constants. The utility function translates the values of the attributes into a *utility score*, which can be used by the buyer to compare bids that are vectors of the three relevant attributes (i.e., quality, quantity, and price). The objective of the buyer is to maximize her total utility from the trade.

Each supplier's production function is also a standard non-linear function, monotonically increasing in quality. We model the cost function as $c_i(q) = A_{1i} q^{\alpha_{1i}}$, where $A_{1i} > 0$ and $\alpha_{1i} > 1$ are quality-related constants for the i^{th} supplier. Each supplier is technologically equipped to produce any quality level from set Q. Since higher quality product requires higher effort and resources, the maximal quantity of production is dependent on the quality of the produced goods according to the production function: $n_i(q) = D - A_{2i} q^{\alpha_{2i}}$, where $A_{2i} > 0$ and $\alpha_{2i} > 1$ are quality-related constants for the supplier and $D > 0$ is a threshold stipulating the maximum units of the commodity technologically possible to produce. The profit function of the suppliers who are awarded a contract is given by

$$\pi_i(p,q,n) = \left(p - c_i(q)\right)n = \left(p - A_{1i} q^{\alpha_{1i}}\right)n,$$

where $0 \le n \le n_i(q)$.

We allow partial fulfillment by assuming the submitted bids to be divisible. This means that the suppliers can offer to supply any number of units, but the buyer makes her decision about the number of units to procure from each of the winning sellers in such a way that maximizes her total utility. We assume that the suppliers will be ready to supply a partial order at the same unit price that they have quoted in their winning bids. This assumption allows us to compare bids by simply calculating the per-unit utility of each bid[7]. Each supplier can have at most one bid accepted; it is the one that generates the highest per-unit utility for the buyer. We call this bid the *best bid* of the bidder. Although the buyer's goal is to maximize her total utility, under the assumption of bid divisibility, the buyer can select individual bids simply on the basis of the per-unit utility generated by the bid.

The outcome of the auction consists of a list of winning suppliers along with the final quality level, the final price that each of them quoted, and the number of units of commodity the buyer decides to procure from each of the winners. We use a first-score rule (analogous to first-price auctions for price-only cases) for winner determination, wherein the winner has to match the exact quality and price listed in his winning bid. This is also referred to as a *discriminatory scoring rule* since all the winning suppliers do not supply at the same price or quality. Although this implies that the buyer may procure the same item with different quality from multiple suppliers, this will not cause a problem since, as mentioned earlier, the range of the quality levels can be set to the accepted tolerance for the product.

Feedback Design

We have developed four feedback schemes that are intended to assist bidders in understanding the state of the auction and in making efficient bids, without revealing the buyer's utility function to the supplier or the supplier's cost schedule to the buyer. Our primary objective is to design assistive information that does not require the buyer or the suppliers to exchange each others' profitability information. Our restrictive information feedback schemes provide provisional allocation information as well as price and quality signals to the bidders. Each of these feedback schemes is described below:

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[7] Without this assumption, winner determination would entail solving a combinatorial problem.

(i) Allocation Signal. These feedback schemes are designed to provide indications to the suppliers regarding provisional allocations.

a. *Rank* refers to the relative ranking of the bid among all the bids received, in terms of buyer's utility. All the best bids are sorted in terms of the per-unit utility derived by the buyer from the bid. This sorted list is then ranked with the bid generating the highest per-unit utility for the buyer having rank 1. The provisional rank of each bidder is disclosed to that bidder at every stage of the auction. Whenever there is a new best bid, the ranks are updated. Multiple bidders can have the same rank if the unit utility scores of their best bid happen to be the same, in which case the remaining requirement is split among them.

b. *Status* is a Boolean variable that indicates to the bidder whether his bid is currently (provisionally) in the winning set. Since we are considering more practical multiple sourcing scenarios, even the bidders ranked second or lower can win a portion of the order if the highest ranked supplier is unable to fulfill the entire order.

(ii) Marginal Utility Signal. These feedback schemes are expected to assist the bidders in formulating optimal bids without explicitly announcing the buyer's utility function. This consists of vectors of marginal values for the quality and price attributes that will be provided to the suppliers in order to help them optimally improve their rank at any given state of the auction if they chose to. This feedback will be provided to all suppliers who are not ranked first.

a. *Price Update* is a vector of possible prices to achieve each rank that is above the bidder's current rank, where quality and quantity levels remain the same as in the existing best bid of the supplier.

b. *Quality Update* is a vector of possible quality levels to achieve each rank that is above the bidder's current rank, where price and quantity levels remain the existing best bid of the supplier.

These vectors would be tailored to the bid specifications of each supplier. Each supplier can weigh these two pieces of information against his own profit function and revise his bid accordingly so as to extract maximum profit. Note that sometimes the suggested quality level or price may not be achievable, e.g., if the suggested ask price for a given quality is below the bidder's cost. In such cases the bidders must use their own judgment to revise price as well as quality in order to place the most profitable bid.

For the purpose of our empirical investigation concerning the impact of these feedback schemes on the dynamics and outcome of the auctions, we arrange the feedback schemes into three progressively advanced feedback levels. These are:

- *Level 1 - RANK*. In this level, only Rank feedback is provided.
- *Level 2 - UTILITY.* In this level, Rank, Price Update, and Quality Update are provided.
- *Level 3 - STATUS*. In this level, Rank, Price Update, Quality Update, and Status are provided.

The levels are named after the additional feedback that is provided at that level. Each of these feedback levels is expected to serve a specific purpose as described below.

The rank of the bidders has been used as a feedback scheme in previous research as well (Koppius and van Heck 2003). We use this feedback level as a baseline. While the RANK feedback provides information regarding provisional allocation, it does not inform the bidders whether, at a given rank, they are included in the winning set or not. Furthermore, if the bidders believe that they are not included in the winning set, they do not have precise information regarding the minimum revision that they need to make to be included in the provisional allocation. The UTILITY feedback is expected to serve this purpose. Simply providing allocation feedback is generally insufficient for decision makers to make myopically optimal decisions (Brehmer 1980), since the feedback lacks strategic information regarding the marginal improvement to the bid that is required. The UTILIY feedback condition provides a higher level of cognitive feedback, offering task-related information, which has been shown to be effective in learning tasks (Balzer et al. 1989) and is expected to lead towards improving individual's economic performance. Therefore, we expect that bidders will be able to gain higher profits with the UTILITY feedback as compared to the RANK feedback. However, even with the UTILITY feedback, suppliers do not have the information as to whether they are winning at a certain rank. Without this critical piece of information, suppliers may end up undercutting their profit in an attempt to achieve a higher rank. Since in Level 3 this crucial feedback is available to the bidders, the STATUS feedback can be expected to lead to higher bidder profits compared to the other two cases. However, at the same time, more transparency may also lead to more competitive bidding, resulting in lower profits for the suppliers. Note that, these three feedback levels are not the only possible combinations of the feedback schemes that we have designed. However, each of them addresses a specific problem that bidders face while composing and revising multidimensional bids.

Performance Measures

The auction literature on multiattrbute auctions provides a variety of criteria and measures to evaluate the performance of procurement auctions (Beil and Wein 2003; Bichler 2000; Bichler and Kalagnanam 2005; Chen-Ritzo et al. 2005; Elmaghraby 2005; Koppius and van Heck 2003; Parkes and Kalagnanam 2005; Pinker et al. 2003; Snir and Hitt 2003). We consider the following criteria and measures, with definitions as appropriate, in comparing auction outcomes under the three different feedback regimes:

- *Allocative efficiency*. The allocative efficiency of a mechanism measures the social welfare from the allocation using the mechanism as compared to the maximum social benefits that could have been achieved. A 100% efficient procurement contract maximizes the joint gains, or welfare, of the buyer and the seller. This metric is of interest to all parties, since a more efficient mechanism can potentially benefit both the suppliers as well as the buyer.
- *Buyer's Utility*. This is the total utility of the buyer from the entire procurement. This metric is of interest to the buyer. In general, a mechanism that generates higher utility would be more preferable to the buyer.
- *Supplier's Profit*. The profit garnered by each supplier who wins a contract is another common performance measure. Bidders may be unwilling to participate in auctions where most of the gains of the trade go to the buyer. One of the reasons suppliers initially resisted implementations of procurement auctions was because buyers tried to design mechanisms that squeezed prices down for the buyer at the expense of the suppliers (Engelbrecht-Wiggans and Katok 2006; Jap 2002). Therefore, even though a buyer would want to maximize her utility, it may still be in her best interest to design a mechanism that leads to a fair distribution of the gains.
- *Auction Duration* (or auction convergence). This is another metric of interest for auctioneers as longer auctions impose greater cost of running it.

Experiments

In order to study the impact of feedback on the dynamics and outcome of the auctions under varying levels of feedback, we conduct a laboratory experiment, wherein subjects participate in hypothetical multiattribute procurement auctions. The hypothetical auction environment is based on the design presented earlier. Each auction was conducted with four, five, or six suppliers. Subjects played the role of suppliers, and a computer program, with a built-in utility function for evaluating bids and providing appropriate feedback, played the role of a buyer.

The parameter values in our model were chosen as follows: $A_0 = 10$, $A_{1i} = 100$, $B = 2.4$, $C = 1$, $D = 200*m$ where m is the number of suppliers in the auction, $A_{2i} = D - 200$, $\alpha_0 = 0.6$, $\alpha_{1i} = 2$, $\alpha_{2i} = 2$, $\beta = 0.3$, $\gamma = 1.05$. These values were selected so as to provide the utility and cost functions their desired characteristics, as discussed earlier, and also to set the Pareto optimal allocations at desired levels in order to accurately measure bidder performance. The values of the threshold D and A_{2i} were adjusted depending on the number of suppliers (as specified above) to maintain similar shapes of the utility and profit curves, and also to ensure that the Pareto optimal allocations are equivalent in each case for easy comparison. The quality levels were translated to a 1 – 100 scale (rather than .01 through 1.00) on the auction interface for easier interpretation by subjects. In all subsequent discussions, we will use this revised quality scale.

The supplier production functions in terms of cost, $c_i(q)$, and quantity, $n_i(q)$, are graphically represented in Figure 1. The quantity curve is shown for the auctions with five suppliers. The downward-sloping quantity curve indicates that, as a supplier improves the quality of his product, he would be able to produce fewer units due to resource constraints. Note that, in order to minimize confounding our comparisons of auction mechanisms with different feedback levels, we chose to conduct the experiments with homogeneous suppliers, i.e., the production functions of all the suppliers participating in the auctions were identical.

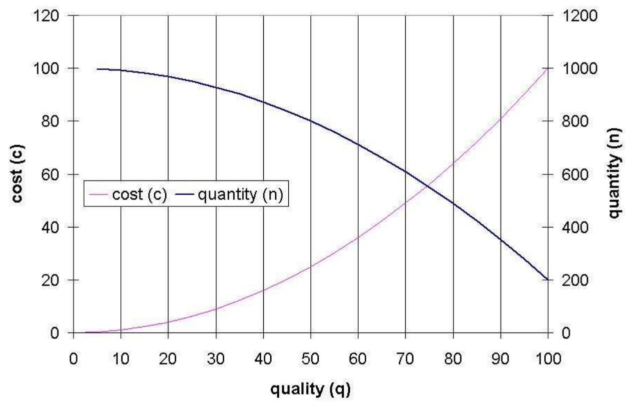

Figure 1. Production functions of suppliers.

The auctions parameters were chosen in such a way that the maximum possible profit margin for the supplier at any quality level was 16.4%, beyond which buyer utility would be negative, i.e., the buyer could not pay a higher price for that quality level. More precisely, the Pareto optimal profit was set at approximately $3,300, which could be earned if each supplier bid at the quality level of 100 and quantity level 200, with 16.4% profit margin. This was Pareto optimal because no bidder could gain by deviating from these specifications without hurting another bidder's earnings. However, myopic profits for each supplier could be maximized at a quality level around 75. The myopic profit maximizing allocation was deliberately set to be different from the Pareto optimal allocation to study whether feedback can lead to a Pareto optimal outcome. The buyer's utility curves and the suppliers' profit curves for the auctions are shown in Figures 2a and 2b respectively.

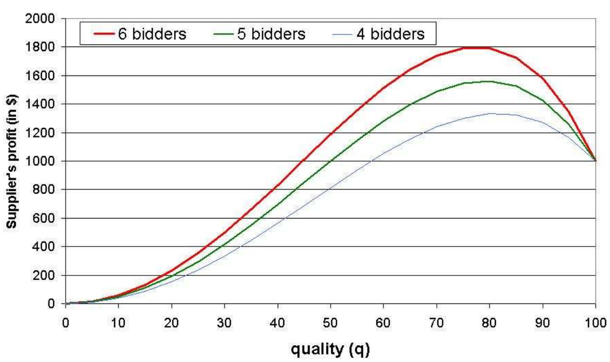

Figure 2a. Supplier's profit function assuming 5% margin.

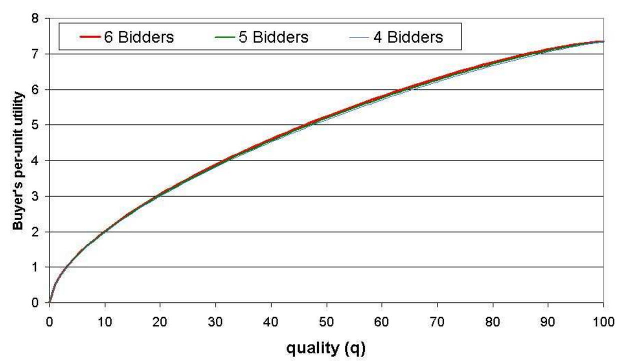

Figure 2b. Buyer's per-unit utility function assuming the supplier extracts 5% profit margin.

The graphs are drawn assuming the supplier bids the maximum allowable quantity for a given quality and asks 5% margin from the trade. The per-unit utility monotonically increases with quality. The three curves in Figure 2b are overlapping.

Experimental Sessions

The three feedback levels described earlier form the three treatments for our laboratory experiments. These are summarized in Table 1. We conducted a total of 37 auctions over 10 experimental sessions. Three to four auctions were simultaneously conducted in each session. The participants in a session were randomly assigned to specific auctions; so, bidders were not aware of the identities of the other bidders they were competing with. The 169 unique participants in 37 auctions were all undergraduate business students who responded to volunteer solicitation announcements throughout the business school. The average age of the subject pool was 21 years; 53% were male. Subjects were not allowed to participate in these experiments more than once. Thus, all our comparisons are between-subject.

Table 1. Feedback schemes for supporting multiattribute auctions.

Treatment	Feedback Type	Description
Treatment 1	RANK	Rank feedback is provided.
Treatment 2	UTILITY	Rank, Price Update, and Quality Update are provided.
Treatment 3	STATUS	Rank, Price Update, Quality Update, and Status are provided.

At the beginning of each session, instructions explaining the rules of the auction were read aloud. The instructions were followed by short tests to familiarize the participants with the rules of the auction as well as the bidding environment. The auctions as well as the tests were entirely computerized.

Auction Rules

Each bidder could have at most one bid – called his *best bid* – accepted at any point during the auction. This was the bid that generated the highest utility for the buyer. Among all the bids placed by a supplier, the one that is most profitable for the buyer was identified to the buyer at all stages. When an auction ended, only the standing best bids of each supplier were used for determining winners; all other bids were ignored.

Each bidder could only see his own bids. As is conventional in procurement auctions of high strategic importance, bidders were not shown the bids placed by other bidders.

A *soft* stopping rule was used, i.e., after an initial time period, the auction ended if no bid that improved the buyer's profit was placed for x minutes. This rule of extending the auction was followed in order to eliminate *sniping*, i.e., placing bids in the last few seconds of the auction. The initial time period was chosen as 14 minutes, with $x = 1$ minute. Consequently, each auction lasted at least 15 minutes. The mean duration of the auctions was 19 minutes.

The compensation scheme of the bidders was a fixed amount of $10 plus an amount based on their individual performances. Bidders were paid in proportion to their profits from the auction. If they were unable to win a contract, their profit was zero; in that case they only received the fixed amount of $10. At the end of a session, participants were paid privately in sealed envelopes.

Auction Interfaces

The auction interface for all three treatments differed only in the type of feedback provided. In all three treatments, only the bids that were placed by that particular bidder were displayed on his screen. It is a common practice in procurement auctions to not disclose competitors' bids. The bids were displayed in reverse chronological order on the auction screen. The total number of units required by the buyer and the number of suppliers competing in the auction to supply the units were disclosed as soon as the auction started.

The interface for the Level 1 feedback is shown in Figure 3. In this as well as in the other cases, the bidders could find their production costs by simply entering the quality level. Furthermore, as soon as they entered the quality level, the maximum quantity that they could produce at their chosen quality level was also indicated to them. This is shown in bold red at the top of the text-box for entering quantity in Figure 3. In keeping with practical auctions, the bidders were not allowed to enter the asking price directly, instead they had to enter their intended profit margin, from which the asking price was automatically computed and displayed by the auction interface. Once a bidder entered quality, margin, and quantity, the potential profit from the chosen specification was displayed to the bidder. Bids could be placed by entering a value for all the three enterable parameters, and then pressing the <Submit Bid> button. The auction interface ensured that only valid values for the enterable parameters were submitted. The standing best bid of the bidder was highlighted at all stages of the auction and the current rank was indicated at the center of the screen. In Figure 3, Bid 10 is the current best bid and current rank of the bidder is 3 (out of 5 participating suppliers). The total elapsed time of the auction and the time since the last bid was placed were also displayed.

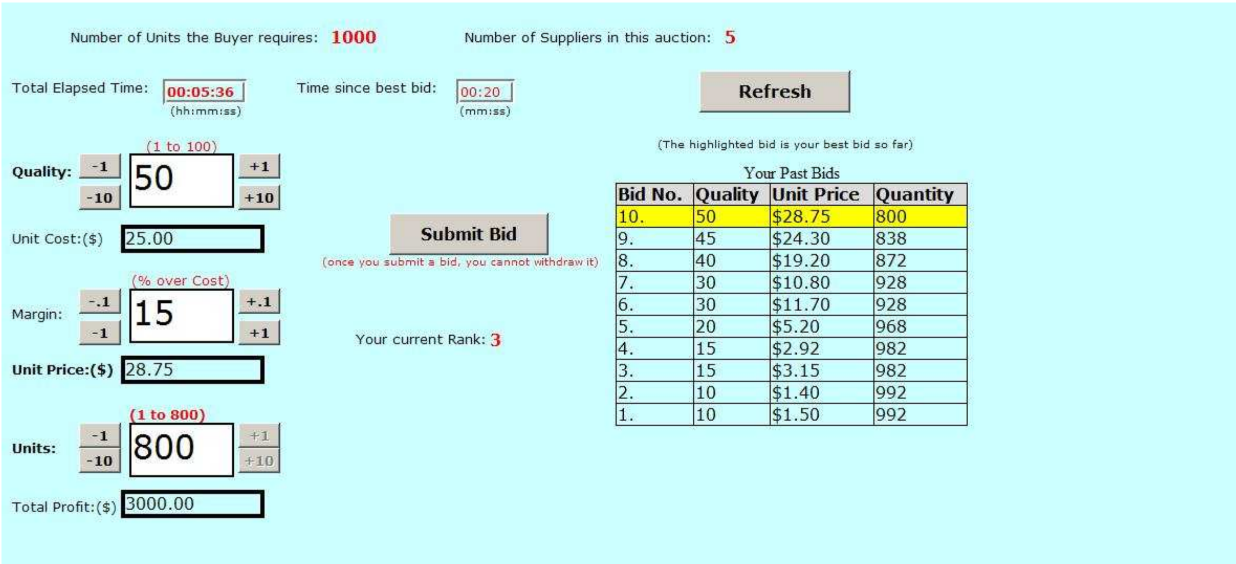

Figure 3. Auction interface for RANK feedback.

In our second treatment, UTILITY feedback was provided. This included Price Update, Quality Update along with Rank. A snapshot of the interface for this treatment is shown in Figure 4. In this example, since the rank of the bidder is 3, suggestions are provided for improving the rank to 2 and 1. The suggestions imply that if the bidder wants to improve his rank to 2, he could reduce his asking price from $28.75 to $27.73 keeping the quality constant at 50; or he could increase the quality level of the bid from 50 to 51, keeping the asking price at $28.75. For computing these suggestions, the quantity in each case was assumed to be the maximum allowed for the chosen quality. The subjects were instructed that these were only approximate suggestions and they might need to update both quality as well as price in order to boost their rank.

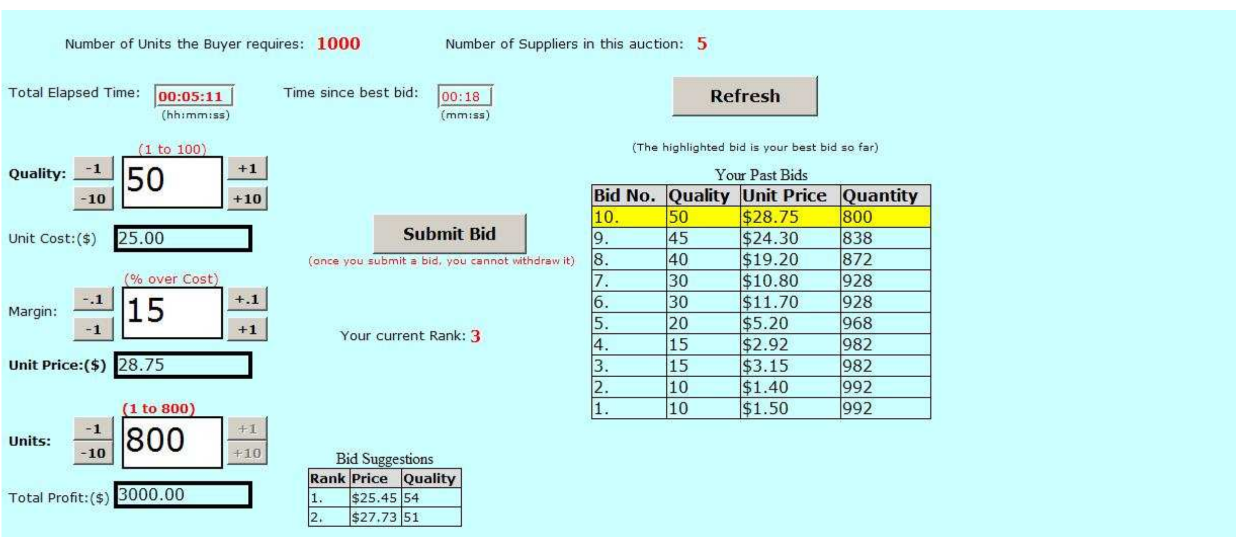

Figure 4. Auction interface for UTILITY feedback.

In our third treatment, in addition to all the information described so far, the Status feedback was provided. The interface for this treatment is shown in Figure 5. The Status feedback is displayed below the rank. In this example, the bidder is not currently in the winning set.

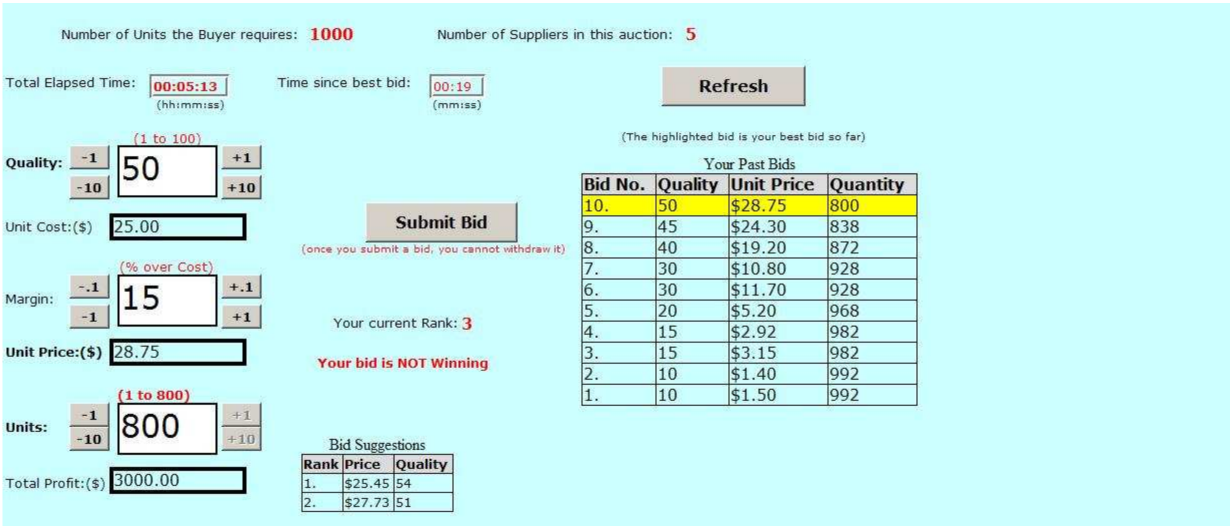

Figure 5. Auction interface for STATUS feedback.

Results and Discussion

Descriptive statistics for several metrics of interest are provided in Table 2. Although mean efficiency increases monotonically with increasing level of feedback, the differences in efficiency between each treatment are not statistically significant at the 95% level. This insignificance is similar to the findings of Bichler (2000), who did not find any significant efficiency difference between price-only auctions and multiattribute auctions even after the buyer's scoring function was revealed to the suppliers. One way to increase the efficiency of the auctions would be for the buyer to provide feedback with information concerning how a supplier can improve his profit while also improving his rank. In other words, overall social welfare can be increased by providing feedback that is directed to increase both buyer's utility and supplier's profit (Chen-Ritzo et al. 2005). However, any feedback that assists the supplier to increase his profit would require the buyer to be familiar with suppliers' profit functions. Our feedback schemes, on the other hand, are designed to minimize the exchange of strategic information between the buyers and the sellers.

The nature of feedback, however, has significant impact on the distribution of the economic surplus of the trade between the buyer and the suppliers. Since there were varying number of suppliers in different auctions (ranging from four to six), we present the total utility of the buyer as a percentage of the maximum possible utility rather than presenting the total raw utility. Buyer's utility is higher in less transparent auctions while suppliers are able to extract higher profits with increasing transparency of the auctions. The duration of the auctions vary with differences in feedback. With STATUS feedback, the auctions complete faster than the other two cases, possibly because bidders are able to place bids with more precision.

Table 2. Descriptive statistics of the auctions.

Treatment	**RANK feedback (Level 1)**	**UTILITY feedback (Level 2)**	**STATUS feedback (Level 3)**
Number of Auctions Conducted (number of participants)	12 (60)	13 (58)	12 (51)
Mean Efficiency (SE)	75.64% (2.12)	76.22% (2.70)	77.74% (2.07)
Mean Buyer's Utility as a Percentage of Maximum Possible Utility (SE)	89.84% (1.71)	88.14% (3.38)	82.94% (4.21)
Mean Supplier's Profit (SE)	$244.41 (38.92)	$328.61 (123.68)	$451.07 (124.58)
Mean Duration in Minutes (SE)	19.12 (1.27)	19.54 (1.58)	17.43 (0.9)

Comparing the three levels of feedback, it appears that the marginal utility signal (Price update and Quality update), which was provided in Levels 2 and 3 but not in Level 1, helps the bidders in placing relatively more profitable bids. With UTILITY feedback, winning bidders, on average, extracted 34% more profit and with STATUS feedback almost 85% more profit than their counterparts in Treatment 1 with just RANK feedback (significant at the 95% level). This indicates that higher transparency in the form of restrictive feedback aids bidders in generating higher surplus for themselves. With price and quality updates, bidders can improve their ranks by revising their bids by the minimum required amounts, even without explicit information regarding the bids of the other bidders. Thus, the utility signals serve the dual purpose of helping the bidders generate more profit for themselves while concealing the bids of the other suppliers.

Neither the RANK nor the UTILITY feedback informs the bidder whether they are in the provisional winning set. Thus, in Levels 1 and 2, bidders who are not ranked one or two, may be tempted to try and improve their ranks even when they are in the winning set. We provide data supporting this conjecture in the following section. With the provision of the STATUS feedback (Level 3), however, bidders know whether they are winning at a certain rank. With the availability of this information, bidders are able to extract 37% more profits than those with UTILITY feedback. However, the significantly higher profits in Level 3 come at the expense of buyer's utility, which drops close to 6% compared to that in Level 2 (not significant at the 95% level). In terms of the duration of the auctions, the most transparent auctions (with STATUS feedback) finish the fastest, most likely because the bidders have to place fewer exploratory bids.

This evaluation of several categories of feedback provide a range of options for sourcing vendors (e.g., Ariba) and other companies, who want to automate their RFQ processes through multiattribute auctions, to choose from. First and foremost, each of the feedback schemes assists bidders in bid formulation without explicitly revealing the buyer's utility function to the suppliers or suppliers' production schedules to the buyer. Secondly, the empirical evaluation of the feedback schemes provides insights regarding the type of feedback to choose based on specific auction objectives. For example, if the auction is for a commodity type product with a large number of suppliers, then the RANK feedback is a better choice for the buyer, since it can foster competition and drive down price. However, with this scheme, companies run the risk of alienating suppliers since bidders are unable to retain much profit for themselves. The importance of long-term relationships in procurement is well established (Ganesan 1994; Monczka et al. 2005). In that respect, the UTILITY or STATUS feedback may be the better choice since they generate relatively more profits for the suppliers. In fact, the UTILITY feedback (Level 2) results in a win-win situation for the buyer and the supplier with only a negligible loss of efficiency (0.7%) compared to the STATUS feedback (Level 3).

In addition to the above metrics, the number of suppliers to whom a buyer hands out a contract is also frequently of interest to buyers. Procuring a commodity from a large number of suppliers is often less risky for a buyer than procuring it from only a few suppliers because in the first case the buyer has more alternatives. In case a supplier is unable to fulfill the contract the buyer can turn to other suppliers. Furthermore, procuring the commodity from a large number of suppliers puts the buyer in a stronger bargaining position. For each level of feedback, we computed the percentage of suppliers who won a part of the contract; these were 85% with RANK, 88% for UTILITY, and 94% with STATUS. Thus, higher levels of transparency resulted in a greater number of winning suppliers. Moreover, 94% winning suppliers in Treatment 3 implies that STATUS feedback led the auctions close to Pareto optimal allocation. Recall, in our setup the Pareto optimal allocation was one where every participating supplier received a contract.

An aspect of the procurement auctions that we did not investigate in this study is how some of the results presented above would change in repeated auctions. Repeated interactions in multiround auctions have been shown to have impact on bidding dynamics leading to differences in the auction outcomes (Fevrier 2003; Jeitschko 1998; Jofre-Bonet and Pesendorfer 2000; Roth and Ockenfels 2006). Bidders learn from their interactions with the mechanism and hence experienced bidders are able to make better use of the information feedback. Future research can test whether efficiency of the auctions increase after repeated participation.

Bidder Behavior

In order to design effective economic mechanisms, it is important to understand the behavior of the agents participating in the mechanisms. We look at several bid characteristics to study differences in bidding behavior among the three feedback regimes. Table 3 displays descriptive statistics on the number of bids per bidder that were placed in the auctions and also the number of provisional best bids. Fewer total bids as well as fewer best bids were placed with increasing feedback. The differences between levels 1 and 2 are not statistically significant. The percentage of *dead bids*, i.e., bids that did not revise the existing best bid of the bidder, also decreased with higher levels of feedback (significant at the 99% level). With more information, bidders appear to be better aware of the state of the auction resulting in more precise bidding. However, even in Treatment 3 (the treatment with most amount of feedback), half the bids were inconsequential. This supports the proposition that even the most advanced levels of feedback (that we tested) does not seem to disclose buyer's and other bidders' preferences to any supplier.

Table 3. Bidding characteristics.

	RANK feedback (Level 1)	**UTILITY feedback (Level 2)**	**STATUS feedback (Level 3)**
Mean Number of Bids per Bidder (SE)[8]	55.10 (8.42)	44.62 (6.45)	30.31 (4.08)
Mean Number of Best Bids per Bidder (SE)	19.28 (7.31)	18.74 (5.41)	15.15 (3.16)
% of Dead Bids (i.e., bids that did not update the existing best bid of the bidder)	65%	58%	50%

Intrabidder dispersion and *interbidder dispersion* have been shown to be relevant metrics for characterizing bid patterns (Nyborg et al. 2002). Intrabidder dispersion is a dispersion measure at the bidder level; given by the standard deviation of bidder i's bids in auction j. Interbidder dispersion is the auction level dispersion, i.e., the standard deviation of all the bids in an auction. We measure these dispersions for both quality and profit margin for the best bids. We do not measure the dispersion of the quantity, since in our setting the number of units the bidders could bid depended on his choice of quality. Similarly, we do not measure price dispersion because, for a given profit margin, price would vary in concert with quality. The results are shown in Table 4.

It is evident that with UTILITY feedback, the means of the two types of dispersions along both the dimensions (quality and margin) are higher than the corresponding figures for RANK and STATUS feedbacks. The likely reason is that, equipped with the marginal prices, bidders in Level 2 placed a large number of incremental bids. However, without the Status feedback, they possibly did not know when exactly to stop. So, they possibly kept on bidding even after they were in the winning set. Although the number of bids placed by each bidder in Treatment 1 was 19% higher than those placed in Treatment 2, the bids in Treatment 1 auctions were likely in smaller increments; which is also the reason for the 7% higher dead bids in Treatment 1.

Table 4. Bid dispersions of best bids.

		RANK feedback (Level 1)	**UTILITY feedback (Level 2)**	**STATUS feedback (Level 3)**
Mean Intrabidder Dispersion	Quality	12.65	14.60	9.75
	Margin	3.78	7.21	4.41
Mean Interbidder Dispersion	Quality	14.77	17.51	13.54
	Margin	5.92	11.38	6.72

Comparing RANK feedback and STATUS feedback cases, we find that the quality dispersions are higher (significant at the 95% level) in the former while margin dispersions are higher in the latter (not significant at the 95% level). While for a given quality, a reduction in profit margin always was more profitable for the buyer, an increase in quality for a given profit margin did not necessarily increase buyer's utility because the increase in quality implied an increase in cost, which for a given margin implied higher price and consequently less utility for the buyer. Thus, with RANK feedback, the percentage of dead bids is relatively higher, as shown in Table 3. The fact that the quality dispersions are higher with RANK feedback than STATUS feedback, while the margin dispersions are lower further emphasizes the hypothesis that bidders in Treatment 1 resorted to relatively more quality updates. The dispersion patterns are very similar even if we include the dead bids.

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[8] Since the auctions were conducted with varying number of bidders, it is more informative to consider number of bids per bidder than the total number of bids per auction.

In summary, the results displayed in Table 4 in combination with those displayed in Table 3, indicate that the bidders in Treatment 1 placed a large number of bids with relatively larger quality variations while in Treatment 2, bidders effectively used the UTILITY feedback to place a large number of marginal bids. With STATUS feedback, bidders placed fewer, more precise bids, manipulating both quality as well as the profit margin. Thus, we find clear evidence that bidder behavior can be significantly influenced by the nature of feedback. Furthermore, the differences in bidding patterns result in differences in economic outcomes. Designers of mercantile mechanisms can exploit these insights to build mechanisms tailored to achieve specific auction objectives.

So far, we have analyzed *how* the bidders revise their bids in each of the three feedback regimes. Next, we analyze *when* the bidders choose to revise their bids. First, we study whether the bidders updated their bids that were already winning (provisionally). These results are shown in Table 5.

Table 5. Winning Bid revisions.

	RANK feedback (Level 1)	**UTILITY feedback (Level 2)**	**STATUS feedback (Level 3)**
Percentage of revised bids that were already provisionally winning	55%	61%	49%
Percentage of winning bid revisions that did not improve supplier's profit	45%	47%	23%

As can be seen, in the two cases where we did not provide the winning status feedback, more than half the bids revised were already winning; 55% in Level 1 and 61% in Level 2. Some of the winning bids were, of course, revised to place more profitable bids; which is why we see that even with the availability of winning status feedback, bidders revised their existing winning bids. However, in the two cases where winning status was not displayed to the bidders (Level 1 and Level 2), a large percentage of the winning bid revisions (45% with RANK and 47% with UTILITY) lowered the supplier's profit. These bids were most likely placed by the bidders to improve their ranks. In fact, the majority of these bids (65% with RANK and 63% with UTILITY) were placed by bidders who were in ranks 3 or below.

But what is even more interesting is that even with STATUS feedback, we find that 23% of the winning bid revisions were unprofitable for the bidders. This observation is contrary to theoretical predictions of bidder behavior, and underscores the importance of conducting laboratory experiments to study bidder behavior. The most likely reason for this departure from theory is that, apart from winning, bidders wanted to achieve higher ranks. It is also possible, that some bidders preferred placing jump bids (akin to *Evaluators* in price-only auctions – Bapna et al. 2000) rather than marginal bids. However, the percentage of unprofitable winning bid revisions in Treatment 3 is significantly less than in the other two cases. This emphasizes the significance of the STATUS feedback, without which the bidders are not sure whether they are winning, and consequently they try to undercut their profit margins in hopes of securing a contract. With the provision of Status feedback, we see a higher number of winners in Treatment 3 compared to the other two cases. As mentioned earlier, in our setup, the Pareto optimal outcome could be achieved when each bidder bid for quality 100, and each proposed to supply equal number of units, i.e., the total quantity required by the buyer divided by the number of suppliers. In order to reach the Pareto optimal allocation, some bidders needed to settle at lower ranks without undercutting their profits in striving to achieve higher ranks. However, without knowledge of the winning status at a lower rank, the bidders sacrificed profit in order to ensure that they end up in the winning set. Based on these observations, we can postulate that, to achieve Pareto optimal outcomes, it is important to disclose provisional allocation information.

Conclusions

Procurement auctions are increasingly becoming a popular sourcing mechanism for firms. Traditional reverse auctions hinder the automation of procurement contracts, which typically have several non-monetary attributes in addition to price. Multiattribute auctions provide a promising extension to the standard auction framework. Theory, practice, and experimental evidence suggest that these auctions, through the use of more expressive bids, can improve the efficiency of procurement for configurable goods and services compared to price-only auctions. However, given the strategic nature of these auctions, the type and amount of information that should be exchanged is not readily apparent, although the transparency of the mechanism has serious profit implications for the buyers as well as the suppliers. From an economic perspective, the challenge is the analysis and derivation of appropriate feedback mechanisms that enable us to achieve specific auction objectives.

In this paper, we extend prior research by designing several feedback schemes for multiattribute auctions with multiple sourcing. An important characteristic of these schemes is that they do not reveal buyer's utility function to the suppliers nor are the suppliers required to disclose their production schedule to the buyer. We also analyze the economic and behavioral implications of different types of feedback using a laboratory experiment with over 150 subjects. Our research contribution is threefold: (1) developing decision support capabilities that can be used by procuring companies and sourcing vendors for running multiattribute procurement auctions, (2) evaluating the decision support schemes using the test bed approach of experimental economics, and (3) understanding the behavior of participants in complex auction environments. The results from our experiments provide us valuable insights on how the nature of feedback influences bidder behavior and the distribution of economic surplus among the buyers and sellers.

Our results show that, in the case of multiple sourcing procurement auctions, it is possible to conduct efficient auctions without exchanging strategic information between the buyer and the sellers. Unlike in the auction of a single item, where higher transparency leads to higher competition and consequently lower supplier profits, in a multiunit auction, with appropriate feedback, both the buyer as well as the sellers are able to extract a share of the gains. With just the rank feedback, the sellers are unable to compose smart bids leaving considerable amount of surplus on the table.

While buyers may be tempted to implement a procurement mechanism that is solely aimed at cost reduction, buyer-supplier relationship may be strained if the suppliers are squeezed out of their profits. In the long run, it is difficult to sustain an economic mechanism where only one party reaps the entire economic surplus. Thus, in the interest of designing sustainable and fair mechanisms, buyers may need to make the environment sufficiently transparent. However, given that procurement is a key source of strategic advantage for many organizations, it is unrealistic to assume that buyers will be willing to disclose their complete preference information to suppliers. Organizations such as Ariba choose a specific information disclosure scheme ranging from high transparency to high opacity depending on the type of the product and the structure of the market. Keeping these practical concerns in mind, we test several feedback schemes and, based on our empirical analysis, provide recommendations regarding the scope of their usage. Future research can test the robustness of these results using different market structures. The results can also be tested in a repeated setting, i.e., a setting where subjects participate in the same treatment multiple times.

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