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DESIGN AND EFFECTS OF INFORMATION FEEDBACK IN CONTINUOUS COMBINATORIAL AUCTIONS

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Abstract

Advancements in information technologies offer opportunities for designing and deploying innovative market mechanisms. For example, combinatorial auctions, in which bidders can bid on combinations of goods, can increase the economic efficiency of a trade when goods have complementarities. However, lack of real-time bidder support tools has been a major obstacle preventing this mechanism from reaching its full potential. This study uses novel feedback mechanisms to aid bidders in formulating bids in real-time to facilitate participation in continuous combinatorial auctions. Laboratory experiments examine the effectiveness of our feedback mechanisms; the study is the first to examine how bidders behave in such information-rich environments. Our results indicate that feedback results in higher efficiency and higher seller's revenue compared to the baseline case where bidders are not provided feedback. Furthermore, contrary to conventional wisdom, even in complex economic environments, individuals effectively integrate rich information in their decision making.

Keywords: Auctions, combinatorial auctions, information feedback, bidder behavior, experimental economics.

DESIGN AND EFFECTS OF INFORMATION FEEDBACK IN CONTINUOUS COMBINATORIAL AUCTIONS

Introduction

Recent advancements in information technologies (IT) present the potential for redesigning market mechanisms to achieve gains for all stakeholders involved (Kambil and Van Heck 1998). Electronic trading institutions can have lower transaction costs and, despite the liquidity advantages of established markets, it is possible for new market institutions to attract a significant amount of trading volume (Clemons and Weber 1996). In addition to cost advantages, new IT-enabled trading mechanisms offer the opportunity to overcome some of the limitations of traditional markets. A prime example is the use of institutional feedback technologies that facilitate buyer-seller transactions by fostering buyer's trust through increased transparency of seller's history (Pavlou and Gefen 2004). Combinatorial auctions (Rothkopf et al. 1998), in which bidders can bid on combinations of goods, embody an innovative new market mechanism that promises to become more practical as IT reduces the costs of computation and information processing that these auctions require.

A combinatorial auction is an auction in which bidders are allowed to bid on combinations of items (frequently referred to in the literature as packages or bundles) as well as on individual items. The primary advantage of combinatorial auctions is that bidders can more fully express their preferences. This is particularly important when some items are complements, i.e., a set of items has greater utility than the sum of the utilities for the individual items. In such cases, economic efficiency is enhanced when bidders are allowed to bid directly on combinations of different assets instead of bidding only on individual items (Hudson and Sandholm 2002).

Combinatorial auctions have received a considerable amount of attention in recent years and have been used in a variety of applications, including the auctioning of the rights to use railroad tracks (Brewer 1999; Brewer and Plott 1996), delivery routes (Caplice 1996; Sandholm 2000), spectrum rights (Cramton 2002; Klemperer 2002; McAfee and McMillan 1996), airport time slots (Rassenti et al. 1982), and the procurement of school meals (Epstein et al. 2002). In each case the compelling motivation for the use of combinatorial auctions was the presence of complementarities among the items that differ across bidders (Cramton et al. 2005).

In spite of their many benefits, one barrier to practical implementations of combinatorial auctions has been the complexity of bid evaluation. Calculating the winning bids at any point even with a small number of items in the auction is a challenging task. In single-item iterative auctions (e.g., English auctions), if a bidder is not the highest bidder, she needs to bid an amount higher than the current highest bid to have a chance of winning the auction. However, in combinatorial auctions this is not necessarily the case. A bid that is not among the current winners can be among the future winners based simply on the combinations of later bids. For example, if we have a 3-item combinatorial auction for selling items A, B, and C, and if the current bids are: (i) $10 for {A, B}; and (ii) $5 for {A}, the second bid is not a current winner, assuming the auctioneer is maximizing her revenue (a standard assumption in the combinatorial auction literature). However, if a new bid of $6 for {B, C} arrives, then Bid (ii) is now among the winning bids.

In traditional single-item auctions, determining the auction's winner and the winning price is a computationally tractable (if not straightforward) problem (Boutilier et al. 1999; Hausch 1986). However, the winner determination problem in combinatorial auctions in general is computationally intractable, i.e., NP-hard (Andersson 2000; Fujishima et al. 1999; Rothkopf et al. 1998; Sandholm 2002; Tennenholtz 2000).

One consequence of the complexity of the winner determination problem is that bidders in combinatorial auctions usually do not have real-time awareness of the current status of their bids, e.g., whether their bids are currently winning or not. In response, researchers have tried to address the winner determination problem primarily in sealed-bid auction settings. Research approaches in iterative combinatorial auctions have primarily focused on creating mechanisms that either handle specific applications or create rules and restrictions to allow several well-defined rounds of bidding. An example of a mechanism for a specific application is the BICAP mechanism created by Brewer and Plott (1996) for the rights to use railroad tracks. Examples of creating specific rules to enable a multi-round computation of the winning bids include Parkes (1999), Ausubel and Milgrom (2002), and Rothkoph et al. (1998). Similarly, Pekeč and Rothkoph (2003) advocated the development of auction mechanisms that identify

discrete rounds with specific rules, making winner determination efficient. However, they noted that, if it was not possible to create discrete rounds, then "*bidtakers should take particular care in providing tools that help bidders in bid preparation*" (pp. 1501).

Such tools have not been available, however; only limited bidder support techniques have been developed. For example, Banks et al. (1989) created a mechanism in which it is the responsibility of the bidders to look at the existing bids and submit a new bid that makes the combined set optimal. Other researchers, such as Nisan (2000), provided bidding languages so that bidders can represent their preferences (bid/item combinations) in sealed bid (non-iterative) auctions. So, it is not surprising that Kwasnica et al. (2005) identified bidder support as the major obstacle for making combinatorial auctions reach their potential, since the availability of increased computing power permits a solution to the winner determination problem for a reasonably-sized problem using commercial software, such as CPLEX (see, for example, Andersson et al. 2000). Our research is focused towards developing meaningful bidder support systems that not only provide bidders with information regarding the status of their bids but also guide bidders in formulating bids in a continuous combinatorial bidding environment.

One aspect of the combinatorial auction research literature is its focus on iterative combinatorial auctions where the auctions proceed for a series of rounds that last for a pre-specified period of time[1]. Several bidders place bids in the same round before the auctioneer ends the round, decides on the provisional set of current winning bids, and updates any information that is provided to bidders. In contrast, we have focused on facilitating real-time bidder support in general *continuous* combinatorial auctions without limiting the scope to a specific application and without imposing restrictive bidding rules, such as discrete bidding rounds. A major difference between our approach and most of the existing approaches is that we provide *real-time* bid evaluation metrics to facilitate continuous auctions that mimic properties of English auctions for a single item.

A major step in the real-time evaluation of combinatorial auctions was taken by Adomavicius and Gupta (2005) in classifying bids into categories and identifying theoretical relationships among them. Based on these relationships, it became possible to define some novel constructs, such as *live* and *dead* bids, which help in developing efficient approaches towards providing answers to various bidding-related queries, e.g., is my bid currently winning? Does my bid stand a chance of winning in the future even if it is not currently winning?

The availability of these constructs provides us the opportunity for conducting continuous combinatorial auctions in real time, similar to ascending English auctions and their counterparts prevalent on the Web. English auctions have several desirable properties; for example, the auction requires minimal bidder sophistication and bidders have limited incentives to invest in acquiring information regarding other bidders' values or strategies. It also allows bidders to formulate simple bidding strategies where they can bid at the currently required bid amount, obtained simply by adding a minimum required bid increment to the standing bid (as long as it is within their valuation of the commodity). Under the common value scenario, an English auction is also likely to produce higher revenues than a sealed bid (first or second price) auction (Banks et al. 2003).

The construction of an information infrastructure for real-time bidder support also raises the issue of the impact of feedback upon bidder behavior. Will bidders be able to properly interpret and synthesize the information available to them in order to formulate optimal bids? It is not often clear whether economic agents will be able to fully integrate all the available information in their decision making. So, another major goal of our research is to analyze the effects of real-time feedback on bidders in combinatorial auctions. Such studies are absent in the literature, primarily because the capabilities have only now been developed to carry out such auctions in real-time and to provide potentially useful feedback, also in real-time, as discussed above.

In order to understand the effect of feedback on bidder behavior in continuous combinatorial auctions, we conduct laboratory experiments with human subjects. We consider a hypothetical auction in which individuals bid on real-estate properties surrounding a lake. Our experimental environment is scalable, allowing different number of items to be sold in an auction and different number of participating bidders. It also provides a plausible scenario in which certain sets of items, e.g., adjacent properties, might have greater value as a set than the sum of their values individually. This auction feature provides the opportunity for combinatorial bidding to offer advantages over traditional, non-combinatorial, single-item bidding. To construct the experimental setup, we relied on theoretical and empirical advances in experimental economics.

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[1] Kwasnica et al. (2005) compare several such mechanisms.

Laboratory data forms an important means of analyzing and comparing complex auction mechanisms. We can test any auction, and with proper control we can calculate performance measures that are impossible in field studies. As Kwasnica et al. (2005) argue: "... *test bed environments in the laboratory [...] exhibit as much complexity or simplicity as one wishes. In these environments, one can test any auction.*" (pp. 421). Several recent studies that have used experimental methodology to test various combinatorial auction designs, primarily in evaluating the design for FCC spectrum auctions, provide a starting point for our research. For example, Ledyard et al. (1997), during the evaluation of proposals for the FCC spectrum auctions, explored whether multiple items should be auctioned sequentially or simultaneously; they also examined the question of whether package bidding should be allowed. They found that simultaneous auctions were a better choice for heterogeneous items and that package bidding is only preferable when there are significant complementarities among items.

Porter (1999) examined the effect of allowing bid withdrawals (at a penalty) to rectify the exposure problem in sequential or simultaneous single-item auctions. The exposure problem occurs in situations where bidders have superadditive valuation for a package but are forced to bid on just the individual items constituting the package. Expectedly, Porter (1999) found that withdrawal leads to higher efficiency and revenue but lower surpluses for bidders. Banks et al. (2003) compared simultaneous multi-round auctions (SMA) with combinatorial multi-round auctions (CMA) and found that CMA outperforms SMA when individuals have superadditive preferences for packages from an efficiency perspective; however, SMA performs better from a revenue perspective while CMA takes more rounds to complete. Kwasnica et al. (2005) proposed a new design called the Resource Allocation Design (RAD) and compared it to Banks et al.'s (1989) Adaptive User Selection Mechanism (AUSM) and the FCC's Simultaneous Multiple Round (SMR) auction described in Milgrom (2004). Kwasnica et al. reported that their design, which provides bidders with price guidance at the end of each round, performs better from the perspective of revenue, efficiency, and the duration of an auction in terms of the number of rounds.

In this study we extend these findings to *continuous* versions of combinatorial auctions, i.e., we allow bids to be placed continuously and not just in discrete iterative bidding rounds. Using novel constructs we develop feedback mechanisms that make this complex trading environment more transparent to the participants. Furthermore, the feedback we provide can guide bidders towards formulating successful bids. We also empirically study the impact of three different kinds of feedback on several economic variables that have been used in the auction literature to compare different trading mechanisms.

Real-Time Bidder Support

We build upon the real-time bid evaluation metrics developed by Adomavicius and Gupta (2005) which can present bidders with price information whenever a bidder wants to explore her alternatives, thereby providing a *continuous* environment. Before describing the details of our modes of feedback, we first provide an overview of the computational real-time bidder support capabilities.

Let I be the set of distinct items to be sold in a combinatorial auction, and let $N = |I|$. We use the terms *auction set* and *auction size* to refer to I and N, respectively. In a combinatorial auction, participants (person, software agent, etc.) can place bids on any *itemset*, i.e., any non-empty subset of I.

An arbitrary bid b can be represented by the tuple $b = (S, v, id)$. Here S denotes the itemset the bid was placed on ($\varnothing \subset S \subseteq I$), also called the *span* of the bid; v denotes the *value* of the bid ($v > 0$), e.g., the monetary amount specified in the bid; and id denotes the *bidder* who submitted this particular bid. Given bid b, $S(b)$, $v(b)$, and $id(b)$ are used to refer to the span, value, and bidder of the bid, respectively. We also use the notion of *auction states* (Adomavicius and Gupta 2005). In particular, auction state k (where $k = 0,1,2,\ldots$) refers to the auction after the first k bids are submitted. The bid set is denoted as B_k, i.e., $B_k = \{b_1,\ldots,b_k\}$. Auction state 0 refers to the auction before any bids are made, i.e., $B_0 = \varnothing$. Obviously, $B_k \subseteq B_l$, for any k and l such that $k \leq l$.

Given an arbitrary set of bids B in a combinatorial auction, a bid set C (where $C \subseteq B$) is called a *bid combination in B* if all bids in C have non-overlapping spans, i.e., for every $b_x, b_y \in C$ such that $b_x \neq b_y$, we have $S(b_x) \cap S(b_y) = \varnothing$. Let C_k denote the set of all bid combinations possible at auction state k, or, more formally, $C_k = \{ C \subseteq B_k \mid b_x, b_y \in C, b_x \neq b_y \Rightarrow S(b_x) \cap S(b_y) = \varnothing \}$.

We assume that the winners of the auction are determined by maximizing the seller's revenue, i.e., $\max \sum_{b \in C} v(b)$, which is a standard assumption in the combinatorial auction research literature. The bid

combination that maximizes this expression is called a *winning bid combination* and is denoted as WIN_k (for auction state k). Moreover, given auction state k, bid $b \in B_k$ is called a *winning bid* in B_k if $b \in WIN_k$. Furthermore, if bid $b \in B_k$ is not a winning bid in B_k and cannot possibly be a winning bid in *any* subsequent auction state then b is called a *dead bid* in B_k. Formally, bid $b \in B_k$ is dead if $b \notin WIN_k$ and $(\forall B_l \supseteq B_k)(b \notin WIN_l)$. The set of all dead bids in B_k is denoted as $DEAD_k$. On the other hand, if $b \notin DEAD_k$ then bid $b \in B_k$ is called a *live bid* in B_k. The set of all live bids in B_k is denoted as $LIVE_k$. Based on the definitions of WIN_k, $DEAD_k$ and $LIVE_k$, it is easy to see that:

- $DEAD_k \cap LIVE_k = \varnothing$ and $DEAD_k \cup LIVE_k = B_k$, i.e., at any auction state k any bid $b \in B_k$ can either be live or dead, but not both.

- $WIN_k \subseteq LIVE_k$, i.e., every winning bid is obviously live.

- $DEAD_k \subseteq DEAD_{k+1}$, i.e., once a bid becomes dead, it can never become live again.

Now, assume that an auction participant is interested in bidding on itemset X. It is important for a bidder to know how much she should bid on X at a given time (i.e., at any auction state k), in order to guarantee that her bid is either winning or at least stands a chance of winning in future (i.e., it is not dead). For this purpose the following bid evaluation metrics are used:

- Bid *winning level* (WL): for itemset X at auction state k, $WL_k(X)$ denotes the minimal value that auction participants have to bid on itemset X in order for this bid to be winning. In other words, after k bids have already been submitted, any bid b_{k+1} on itemset X that has value above $WL_k(X)$ will be winning, i.e., $b_{k+1} \in WIN_{k+1}$.

- Bid *deadness level* (DL): for itemset X at auction state k, $DL_k(X)$ denotes the minimal value that auction participants have to bid on itemset X in order for this bid to be live. Similar to above, after k bids have already been submitted, any bid b_{k+1} on itemset X that has value above $DL_k(X)$ will be live, i.e., $b_{k+1} \in LIVE_{k+1}$.

We will explain these concepts with an example. Let us suppose that we have a 3-item auction with the items being A, B, and C. Table 1 shows the status of all the placed bids at an auction state $k=5$. Bids 1 and 4 form the *winning* bid combination at the current state of the auction, with total revenue of $25, which is greater than that of any other bid combination.[2]

Table 1. Example of bid status

Bid sequence	[bundle; bid]	Status after 5 bids
1.	[A; $10]	Winning
2.	[AC; $20]	Dead
3.	[C; $11]	Live
4.	[BC; $15]	Winning
5.	[AB; $13]	Live

Bid 2 is *dead* because the combined revenue from the bids on {A} and {C} is greater than that of package {A, C}, so this bid cannot win at any subsequent state of the auction. Bids 3 and 5 still have the chance to end up in winning combination depending on subsequent bids (e.g., a new bid of $13 on {C} would make bid 5 *winning*) and hence are still *live*. Now, suppose a bidder wants to bid on item {B}. The winning and deadness levels for this bid are shown in Table 2. Since no bid on {B} has been placed, the DL on that bundle is $1, assuming integer bid increments. The winning level of {B} is $5 because that is the minimum bid required to make it a winning bid along with bids on {A} and {C}.

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[2] The reader might recall that "bid combination" by our definition refers to a set of bids with non-overlapping items.

Table 2. Example of bid evaluation metrics

Bundle	Deadness Level (DL)	Winning Level (WL)
{B}	$1	$5

These metrics provide the opportunity for conducting continuous combinatorial auctions in real time, similarly to ascending English auctions and their counterparts. By analyzing how incoming bids affect the auction dynamics, Adomavicius and Gupta (2005) proved numerous theoretical properties of the above bid evaluation metrics. For example, it was shown that in a combinatorial auction of size N it is possible to have up to 2^N-1 live bids at the same time. On the other hand, there can never be more than N winning bids at any auction state. This illustrates the inherent complexity of combinatorial auctions, and emphasizes the need to have real-time support capabilities to help bidders sort through the existing bids as well as to provide guidance in formulating new bids.

Types of Feedback

The computational infrastructure derived from the concepts presented above allows us to provide different pieces of information to bidders that could potentially be useful in planning and executing their bidding strategies. This brings up the issue of the impact of providing different amounts of this information as feedback to the bidders. To the extent that the bidders can take advantage of this information, we would expect performance to increase, i.e., we expect more efficient bidding, better outcomes for the bidders, and greater satisfaction from the bidders with the process. The one caveat is in terms of the bidders' abilities to incorporate the information. It is not readily apparent to what extent bidders will be able to exploit the information provided to them in formulating their bids. In addition, it is also not clear how the gains of trade will be distributed between the seller and the buyers as a function of the quantity of feedback provided. We propose to test the impact of three cumulative levels of feedback:

- *Level 1: Baseline feedback* (control). This represents the continuous combinatorial auction setup where all submitted bids are visible to all bidders, but no other feedback is provided.

- *Level 2: Outcome feedback*. This level includes all feedback provided in Level 1 plus the currently winning bid combination, i.e., at every auction state the bidders will be aware of which bids would win if the auction ended right then. The currently winning bid combination represents non-trivial feedback, since winner determination in combinatorial auctions is a very computationally complex problem, as mentioned earlier.

- *Level 3: Process feedback*. This level includes all feedback provided in Level 2 plus deterministic bid evaluation metrics. Such metrics include bid deadness levels (i.e., bid levels below which bids can never be part of a winning bid combination) and bid winning levels (i.e., bid levels above which bids become part of the set of currently winning bids) for every possible itemset. This feedback is expected to direct the bidder toward formulating successful bids.

Measuring the performance of bidders with progressively advanced levels of feedback is important because researchers across disciplines (see for example, Grise and Gallupe 2000; Jacoby 1984; Schick et al. 1990; Sparrow 1999) have found that the quality of decisions (or reasoning in general) of an individual correlates positively with the amount of information he or she receives – up to a certain point. If further information is provided beyond this point, the performance of the individual will rapidly decline (Chewning and Harrell 1990). The individual will no longer be able to properly interpret, synthesize, and integrate the information into the decision making process (O'Reilly 1980). A diminished decision quality may result when supply of information exceeds the information processing capacity of an individual (Malhotra 1982).

Performance Measures

When choosing an auction design, a variety of criteria and measures may be used. In general, there will be tradeoffs among these measures. For example, high efficiency may sometimes come at the cost of seller revenue and the time to complete the auction (Banks et al. 2003). We looked at a number of dependent variables for studying auction performance as well as the behavioral impacts of different levels of feedback. Specifically, the following

variables, with definitions as appropriate, were among those measured, collected, or computed during the experimental auctions:

- *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. An auction is said to be 100% efficient when it assigns the set of offered items so that the total value that society obtains from the items is maximized. This happens when each bidder in the auction makes a purchase that is contained in her optimal allocation. Efficiency is the most obvious choice of a performance measure. It was, in fact, the original policy goal of the FCC PCS auction design (Ledyard et al. 1997). We compare the allocations of our various treatments as the percentage of the maximum possible gains that are realized by the allocation process.

Note that the absolute value of efficiency is deceptive because it could be easily increased, for example, by increasing the valuation of the assets. However, we are interested in comparing efficiency across treatments where everything else besides feedback is kept the same.

- *Seller's Revenue*. The seller's revenue in an auction is of interest to an auctioneer. The amount of revenue generated from a particular auction mechanism partially depends on the distribution of the asset valuations across bidders. This distribution again changes when the number of bidders participating in the auction changes. However, in our experiments the number of bidders and the distribution of the valuations are held constant across treatments. Hence the generated revenue from all the treatments can be easily compared. While a more competitive environment may yield higher revenues, a less information-rich environment may yield higher revenues depending upon bidders' risk preferences.

- *Bidder's Profit*. Each bidder's profit from participating in the auction is another common performance measure. Bidders may be unwilling to participate in auctions where the entire surplus goes to the seller. We measured individual bidder surpluses in each of the auctions we conducted.

Based on the literature concerning the general effects of different forms of feedback, it is expected that outcome feedback will not show an advantage over the control condition (Brehmer 1980). With outcome feedback, the bidders would have knowledge of whether their bids are winning or not, and also which bids are currently winning but would have to figure out by themselves the amount that need to be bid in order for their bid to win. Simply providing outcome feedback is generally insufficient for decision makers, needed is more strategic feedback tied to the decisions being made. The process feedback condition provides such cognitive feedback; in particular, the process feedback is task information, which has been shown to be effective in learning tasks (Balzer et al. 1989) and is expected to lead to improved performance. So, we believe that just providing outcome feedback will not help bidders move closer to their optimal allocation of goods. With process feedback, however, all dead bids are removed. So, bidders would have precise information regarding the set of bids that are live at any state of the auction. Consequently they can be expected to formulate bids that together with some other existing live bids can become winning. In addition, once a bidder chooses a bundle of interest, she would be provided with the exact amount that she needs to bid on her chosen bundle in order to win at that state of the auction. This, we believe will help the bidder to move closer towards her optimal allocation. Therefore, we plan to test the following propositions:

Proposition 1: The efficiency in the case of outcome feedback will be similar to that in the case of baseline feedback.

Proposition 2: The efficiency in the case of process feedback will be higher than that in the case of baseline feedback.

With outcome feedback the bidders are aware of whether any of their bids are currently winning or not. So, a utility maximizing bidder can be expected to iteratively increase her bid at least as long as none of her bids are winning or her maximum valuation is reached. We propose that such behavior will result in higher overall revenue of the auction compared to the baseline case. Similarly, process feedback is expected to yield higher revenues as well. This leads us to the following propositions:

Proposition 3: The seller's revenue in the case of outcome feedback will be higher than that in the case of baseline feedback.

Proposition 4: The seller's revenue in the case of process feedback will be higher than that in the case of baseline feedback.

In addition, since process feedback equips the bidders with information regarding the exact bid needed in order to win at the current state of the auction, the bidders can be expected to not overbid on any of the chosen itemsets. This is in contrast to the case of outcome feedback, where bidders are not provided the information regarding exactly how much to bid on the chosen combination. Consequently, we propose that the revenue in this case will be higher due to overbidding.

Proposition 5: The seller's revenue in the case of outcome feedback will be higher than that in the case of process feedback.

Although outcome feedback alone is not expected to increase the efficiency of the auctions, for reasons stated earlier, it is expected to increase the total revenue. This increased revenue, we propose, will come at the expense of bidder profits. So, the bidders' profits in the case of outcome feedback will be lower than in the case of process feedback. In the case of process feedback, equipped with information regarding deadness levels and winning levels, bidders can be expected to bid the minimum required to win, thus maximizing their profits. So, our final propositions are:

Proposition 6: The bidders' profits in the case of outcome feedback will be similar to those in the case of baseline feedback.

Proposition 7: The bidders' profits in the case of process feedback will be higher than those in the case of outcome feedback.

We conducted experiments with human subjects to test these propositions. In the following section we describe our auction design.

Auction Design

To construct the experimental setup, we rely on theoretical and empirical advances in experimental economics. One of the important issues is to create appropriate incentives for bidders to participate in the experiment with economic gains and/or losses in mind. An economic experiment consists of agents (e.g., buyers and sellers) and market institutions (e.g., different types of auctions). For an experiment that takes place in a controlled economic environment of a laboratory to have general theoretical implications, one cannot rely on deductive logic. Instead we have to rely on the general principle of induction, which maintains that behavioral regularities will persist in new situations as long as the relevant underlying conditions remain substantially unchanged.

We rely on Smith's (1976) induced-value theory that identifies sufficient conditions for experimental control. The key idea is that the proper use of a reward mechanism allows an experimenter to induce pre-specified characteristics in experimental subjects. Proper use is further defined to consist of a monotonic non-satiable utility for the reward and that the incremental reward a person receives depends on her actions (and those of other agents) as defined by the institutional rules that she understands. The use of real currency is known to satisfy these important conditions. Furthermore, Jamal and Sunder (1991) find that such salient rewards tend to increase the reliability of results. Smith and Walker (1992) provide a summary of evidence that further supports the use of real monetary rewards in experimental economics. We borrow significant design aspects from researchers who have conducted experiments in the field of combinatorial auctions and use the information regarding the various treatments that have been used in prior literature summarized earlier (e.g., Banks et al. 2003).

Hypothetical Auction Environment

In our experimental environment, three bidders compete to acquire six property lots surrounding a lake. The lots are adjoining and successively labeled A through F, so that Lots A and F are also adjoining. This is shown in Figure 1.
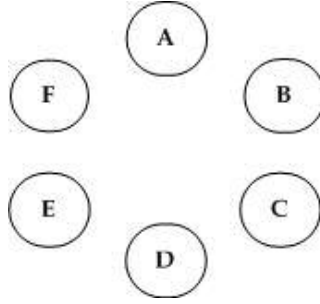
Figure 1. Property lots surrounding a lake

Each bidder has a preferred lot: Bidder 1 prefers Lot A, Bidder 2 prefers Lot C, and Bidder 3 prefers Lot E. For each bidder, the valuation associated with the preferred lot is set at 100; the lot value decreases by 50% as the lot is further from the preferred position. This particular setup is symmetric, with each bidder facing similar valuations relative to the others, allowing them to be treated equivalently in the analyses. Consequently, any consistent differences in behavior among auctions with differing levels of feedback can be reasonably attributed to varying responses to feedback. The valuations of the individual lots for each bidder are as identified in Table 3.

Table 3. Valuations of individual lots for each bidder

	Lot A	Lot B	Lot C	Lot D	Lot E	Lot F
Bidder 1	100	50	25	12.5	25	50
Bidder 2	25	50	100	50	25	12.5
Bidder 3	25	12.5	25	50	100	50

The other key feature of this scenario is that having adjoining lots increases the combined value of the lots by 10% (for every additional adjoining lot) thereby creating superadditive valuations. For example, suppose that Bidder 1 is interested in Lots A and B, and Bidder 2 is interested in Lots C, D, E, and F. The resulting valuations are $(100 + 50) * 1.10 = 165$ for Bidder 1 and $(100 + 50 + 25 + 12.5) * 1.30 = 243.75$ for Bidder 2. Some more examples of how the superadditive valuations will be generated for Bidder 1, whose valuations are presented in Table 3, are shown in Table 4.

Table 4. Examples of superadditive valuations for Bidder 1.

	Lots	Adjoining lots	Valuations for Bidder 1
Example 1	{AB}	2 adjoining	$(100 + 50) * 1.1 = 165.00$
Example 2	{AF}	2 adjoining	$(100 + 50) * 1.1 = 165.00$
Example 3	{CDE}	3 adjoining	$(25 + 12.5 + 25) * 1.2 = 75.00$
Example 4	{BEF}	1 separate; 2 adjoining	$50 + (25 + 50)*1.1 = 132.50$

Note that this scenario is similar to the experimental environment of Banks et al. (2003). The aforementioned example can be generalized with a set of parameters where the valuation of an itemset can be defined as:

$$V_{i\Omega} = \sum_{j \in \Omega} v_{ij} + A_i \sum_{j \in \Omega} \sum_{\substack{k \in \Omega \\ k > j}} s_{jk}$$

where $V_{i\Omega}$ is the value of itemset Ω for individual i. Here itemset Ω is represented by an ordered set of items; v_{ij} is the valuation of item $j \in \Omega$ by individual i; A_i is the maximum superadditivity factor for individual i; and s_{jk} is the strength of relationship between two items of an itemset. For example, if $s_{jk} = 1$ (say, for adjacent items j and k), the total value of a package just consisting of these two items would be $(v_{ij} + v_{ik} + A_i)$. Such a setup allows both for a

compact description of the scenario that can be provided to bidders participating in the auction as well as for building a simulation of the auction environment. We conducted several simulation runs with computerized bidding agents as well as several pilot tests with human bidders to refine the parameters of our model before carrying out our main experiments.

Auction Rules

In the auctions, bidders were allowed to place any number of bids on single lots as well as any combination of lots. They were able to update their previous bids by placing a higher bid on the same bundle. At the end of the auction, the bids that maximized the seller's revenue were determined, and the participants were notified of the result along with their individual profits based on the final allocation. In addition to these general rules, we adopted the following specific rules:

- *Bid increments:* The bid increment was set at $1. The auction interface ensured that only integer (dollar amount) bids could be submitted.

- *Bid withdrawals:* As in most online auctions, participants were not allowed to withdraw their bids.

- *Stopping rule:* A "soft" stopping rule was used, i.e., after an initial time period, the auction ended if no new standing bids were 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 13 minutes, with *x* = 2 minutes. So, each auction lasted at least 15 minutes.

A summary of the auction parameters is shown in Table 5.

Table 5. Auction rules

Number of items up for sale in each auction	6
Number of bidders competing in each auction	3
Duration of each auction	Minimum of 15 minutes. After the first 13 minutes, two minutes from the last bid.
Superadditive valuation	10% on top of the additive valuation of the adjoining lots for every additional adjoining lot.
Bid withdrawals	Not allowed.
Bid increment	$1

Bidders were explained how the valuations were generated. The auction interface allowed them to find their individual valuations for any package. The bidders were not given any fixed budget but the final compensation scheme was based on their individual performances in terms of their retained surplus. Bidders were paid for the lots they won in proportion to their profits from the auction. Profit was calculated as the difference between their valuation of the item(s) and their winning bid(s). Consequently, their profits were positive, zero, or negative depending on whether their winning bid was less than, equal to, or greater than their valuation. Obviously, if they did not win any lot, their profit was zero. Each subject was paid an up-front sum of $10 for participation. Freidman and Sunder (1994) recommend this practice for three reasons: (a) to reduce tardiness, (b) to establish ex ante credibility with the subjects that the rewards being promised to them will be paid to them promptly, and (c) to provide an initial cushion of wealth they can afford to lose in the actual experiment without dipping into their own wallets. At the end of the auction, auction participants were paid 20 cents for every experimental dollar of their profit. Similarly, they were charged 20 cents from their participation fee for every dollar of loss they incurred by bidding above their valuation. The maximum amount that could be taken off was their participation fee.

Auction Interface

The auction interface for all three treatments (i.e., feedback levels) was the same except for the type of

feedback provided. The interface for the Level 1 feedback is shown in Figure 2. In this case, all bids were displayed with the bidder's own bids highlighted on her own screen. The bidders' valuations for the individual lots were displayed on their screens at all times. The bidders could find their valuations for any possible combination of the lots by just clicking on the checkboxes corresponding to each lot. For example, if a bidder clicked on the checkboxes corresponding to Lots B and C, the valuation of the package {B, C} ($165 in Figure 2) would display on the textbox in the center. Bids could be placed by selecting the lots, entering a bid amount, and then pressing the <Submit Bid> button. The total elapsed time of the auction and the time since the last bid was placed were also displayed.

Figure 2. Auction interface for baseline feedback

In our second treatment, in addition to displaying all the bids, the winning bids at any given state of the auction were identified. This interface is shown in Figure 3. At any given point of the auction the bidders knew whether any of their bids were winning or not. Of course, the set of winning bids could change with every new bid. In Figure 3, Bids 3 and 5, identified in bold red, are the winning bids at the given state of the auction.

Figure 3. Auction interface for outcome feedback

In our third treatment, we provided process feedback to bidders in order to help them formulate their bids. As mentioned earlier, this consisted of a specification of the: 1) deadness level – the minimum amount they needed to bid in order for their bid to stand a chance of winning in future given all the other bids at that state of the auction, and 2) winning level – the minimum they needed to bid in order for their bid to be winning at that state of the auction for any package that they chose to bid on. These two amounts provided a range of values for a utility-maximizing bidder to bid on their selected packages. If they bid below the deadness level, that bid would lose in any future state of the auction. So, for any package, the deadness level provided a lower bound for a bidder to bid. In

addition, as in English auctions, the bidders had no incentive to bid above the winning level, which thus provided a likely upper bound. All dead bids, i.e., bids that stood no chance of winning at any subsequent state of the auction, were removed from display. The interface for this treatment is shown in Figure 4.

Figure 4. Auction interface for process feedback

A bidder could find these two bounds for any possible package by simply clicking on the lots constituting the package. In the snapshot of Figure 4, the deadness level for package {C} is $51[3] and the winning level for the package is $56[4], as displayed at the bottom left hand corner. In the bid history table of Figure 4, Bids 4 and 5 are not displayed because they are dead, i.e., they stand no chance of winning in any future state of the auction.

Experimental Sessions

We conducted a total of 53 auctions over 16 experimental sessions. Three to four auctions were simultaneously conducted in each session. The 159 unique participants in the 53 auctions were all undergraduate business students who responded to volunteer solicitation announcements throughout the campus. The average age of the subject pool was 20 years; 55% were male. The participants in each session were randomly assigned to a particular auction. They were not told how many other participants they were competing with, which is in keeping with practical online auctions where bidders are usually unaware of the number of people interested in the commodity. Subjects were not allowed to participate in these experiments more than once. Each session lasted close to two hours on average. In each session, prior to the beginning of the auctions, instructions explaining the rules of the auction were read out loud so that everyone could hear. The instructions were followed by short tests to ensure that the participants understood the rules of the auction as well as the bidding environment. Although the mechanism to generate the valuations of the lots was common knowledge, the distribution of the preferred lots (shown in Table 3 above) was not disclosed. So, each bidder in an auction knew what her preferred lot was but had no knowledge of what the preferred lots of the other bidders were. At the end of the auctions, participants were paid privately in sealed envelopes.

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[3] It is actually anything greater than $50 but since we only allowed integer bids, i.e., bid increments of $1, it is $51.
[4] It is actually anything greater than $55 but since we only allowed integer bids, i.e., bid increments of $1, it is $56.

Results and Discussion

Descriptive statistics for allocative efficiency, seller's revenue, and bidder's profits for the auctions are provided in Table 6. We have excluded 4 auctions from our initial analysis because in these at least one bidder mistakenly placed a bid *significantly* above her valuation. They immediately notified us of the mistake but, since our design disallowed bid withdrawal, rectification of the user error was not possible. Two of those cases were in the control case, i.e., baseline feedback treatment, and one each in the other two treatments.

Table 6. Descriptive statistics of the auctions

Treatments	Number of Auctions Conducted	Mean Efficiency	Mean Seller's Revenue	Mean Bidder's Profit
Baseline Feedback	16	84%	$356.31	$22.74
Outcome Feedback only	16	91%	$410.50	$20.95
Process Feedback	17	92%	$380.71	$28.07

The average efficiencies and the average revenues are both higher in the case of the auctions with feedback than in the baseline case. The mean auctioneer's revenue is highest in the case of outcome feedback, while the mean profit generated by the bidders is highest in the process feedback case. The efficiencies of the outcome and process feedback cases appear to be comparable. One interesting aspect is that, while process feedback (which provides the most amount of information to the bidders) maximizes efficiency and bidder's profit compared to the other two treatments, seller's revenue appears to be maximized through partial feedback (i.e., outcome feedback).

In order to test the significance of our propositions, we conducted Mann-Whitney Rank Sum tests. This test is a non-parametric counterpart of the unpaired *t*-test. It is preferred for smaller samples where the populations are not normally distributed. When comparing data generated from human subjects, it is typical to assume that the data do not meet the normality assumptions required for a *t*-test (see for example Kwasnica et al. 2005; Porter 1999). The rank sum test requires the two samples to be independent, and the observations to be ordinal (Siegel and Castellan 1988), which is exactly the case for the data we are comparing.

Table 7. Mann-Whitney test results

Performance measures Treatments compared	Efficiency	Seller's Revenue	Bidder's Profit
Baseline Feedback vs Outcome Feedback	$z = 1.813$ $p = 0.034$	$z = 2.262$ $p = 0.011$	$z = 0.344$ $p = 0.365$
Baseline Feedback vs Process Feedback	$z = 1.917$ $p = 0.027$	$z = 0.937$ $p = 0.174$	$z = 0.465$ $p = 0.321$
Outcome Feedback vs Process Feedback	$z = 0.221$ $p = 0.412$	$z = 0.613$ $p = 0.269$	$z = 0.743$ $p = 0.228$

The results from the Mann-Whitney tests are provided in Table 7. The results show that either form of feedback – outcome or process – results in a significant improvement in auction efficiency. Thus, our proposition regarding the positive impact of process feedback on efficiency (Proposition 2) is verified. However, even outcome feedback, which we did not expect to have a significant impact on efficiency (Proposition 1), had a significant positive effect on efficiency. The bidders evidently were able to use the information regarding the currently winning bids to formulate winning bids that were closer to their own optimal allocation. Consistent with Proposition 3, the seller's revenue significantly increased with outcome feedback. However, contrary to Proposition 4, seller's revenue did not significantly increase with process feedback. In addition, the difference in revenue between the two

treatments with feedback was not significant (Proposition 5). The reason that process feedback generates lower revenue than outcome feedback is because, with similar efficiency, the surplus in the former case is mostly extracted by the bidders. Therefore, bidder profits are higher in the case of process feedback.

We further investigated why the difference in bidders' profits does not appear to be statistically significant. Upon closer examination of bidding data, we found that there are nine auctions where bidders incurred losses, i.e., they bid above their valuations. This caused a large variance in the profit measure resulting in statistical insignificance. Since we provide fixed valuations (as opposed to a distribution of valuations) for all possible lots to the bidders, it might seem surprising that some bidders still bid above their valuation, especially because in our payoff scheme bidders lost a part or whole of their initial endowment (participation fee) if they bid above their valuation. However, in addition to the fact that we did not allow bid withdrawal, violation of normative principles in competitive auctions is well documented in the literature (e.g., Budescu and Maciejovsky 2005). Therefore, we decided to remove these auctions from further analysis, attributing the irrational bids to bidding errors. Out of the nine auctions that we excluded, four were in the baseline case, one in the outcome feedback case, and four in the process feedback case. Table 8 shows the descriptive statistics and Table 9 presents the results from statistical tests on this modified data set.

Table 8. Descriptive statistics of the remaining auctions

Treatments	Number of Auctions remaining	Mean Seller's Revenue	Mean Bidder's Profit
Baseline Feedback	12	$337.00	$36.38
Outcome Feedback only	15	$407.53	$21.57
Process Feedback	13	$346.69	$41.78

Table 9. Mann-Whitney test results after excluding auctions with bidder losses

Treatments compared	Seller's Revenue	Bidder's Profit
Baseline Feedback vs Outcome Feedback	$z = 2.780$ $p = 0.002$	$z = 1.627$ $p = 0.051$
Baseline Feedback vs Process Feedback	$z = 0.544$ $p = 0.293$	$z = 0.549$ $p = 0.291$
Outcome Feedback vs Process Feedback	$z = 1.636$ $p = 0.050$	$z = 2.085$ $p = 0.018$

The results after the exclusion of nine auctions indicate that providing outcome feedback results in significantly higher revenues for the seller as compared to process feedback, while process feedback results in significantly higher profits for the bidder as compared to outcome feedback (Proposition 7), even though contrary to Proposition 6, outcome feedback resulted in higher bidder's profits. We believe that these results shed valuable insights for mechanism designers regarding the choice of information revelation. Our results indicate that outcome feedback should be used when the goal is to maximize sellers' profit while process feedback should be used when the overall goal is to maximize social welfare. Note that the allocative efficiency is significantly higher in either case compared to the control case.

Apart from the fact that the bidders with Level 3 feedback (maximum feedback) generate significantly higher surplus for themselves than those with the other types of feedback, various other statistics also indicate that the bidders were using the feedback provided to them. For example, the percentage of dead bids in the case where we suggested the winning the deadness levels was significantly lower than the other two cases. In addition, the amount the bidders bid above the minimum levels was significantly lower in the case where these levels were provided as feedback.

Conclusion

IT is being increasingly used to automate existing market processes, but it also presents opportunities to design and deploy new, innovative market mechanisms. Combinatorial auctions, for example, represent such a class of sophisticated trading mechanisms that allow bidders to consider dependencies among the items. Theoretically, this allows advantages over the classical single-item auctioning of multiple items via multiple auctions by ensuring that bidders can consider superadditive valuations, i.e., *valuation*($A + B$) > *valuation*(A) + *valuation*(B). However, the inability to provide meaningful feedback in real-time has resulted in limited application of such auctions as continuous mechanisms where bidders update their bids continuously and not just in discrete rounds. One of the primary characteristics of most online auction institutions is that they are continuous. A basic requirement for generating bidder participation in such auctions is the availability of information regarding the current state of the auction, e.g., identification of the currently winning bid(s). While online auctioneers have implemented many different variations of classical single-item auctions (including auctions with multiple units – see, for example, Bapna et al. 2003), there have been no widespread implementations of continuous combinatorial auctions to sell multiple items to multiple bidders. This leads Kwasnica et al. (2005) to assert that supporting bidders in combinatorial auctions is the next big challenge in facilitating wider use of combinatorial auctions.

The contributions of this paper are threefold: 1) we design novel feedback mechanisms that can aid bidders in formulating successful bids; 2) we empirically demonstrate the effectiveness of the feedback mechanisms in increasing social welfare, generating higher revenues for the seller, and in some cases, more profits for the buyer; 3) we build valuable insights for mechanism designers to choose an appropriate level of feedback for specific auction objectives. We studied the comparative benefits of each level of feedback with respect to traditional metrics of interest, such as efficiency, revenue, and bidder profits. In order to study these features, we first developed a simulation testbed that facilitated the creation of a robust experimental environment, including the appropriate choice of parameter values so that relevant effects could be isolated with minimal noise due to experimental instrument bias. Using the experimental environment, we empirically examined real bidder behavior. The results from our study provide important theoretical contributions, advancing our knowledge of bidder behavior in combinatorial auctions and adding to the active experimental exploration and design of new combinatorial auction mechanisms. Our results provide mechanism designers the knowledge to choose a suitable level of feedback for specific auction objectives. For example, if the goal is to maximize allocative efficiency, then the designer should choose process feedback, whereas if the goal is to maximize seller's revenue then outcome feedback should be preferred. Also, providing higher level of information is a preferable choice for all stakeholders because, even though with full information bidders are able to extract higher surplus, higher efficiency results in higher revenue for sellers as compared to the limited-information baseline case.

The spread of the Internet has led to an expansion of online auctions as a retail mechanism for both Business-to-Consumer (B2C) and Consumer-to-Consumer (C2C) commerce. To date, such auctions have generally used non-combinatorial, single-item bidding mechanisms, having employed many different variations of this class of mechanism. The use of continuous combinatorial auctions to sell multiple items to multiple bidders has only recently begun to be explored. Our study is designed to enhance our knowledge concerning bidder behavior in combinatorial auctions. The study is also the first to examine how bidders use information richness in complex environments. Once these issues are better understood, it is expected that these mechanisms will become more widespread in B2C and in C2C commerce. Therefore, our research has a potential to facilitate the introduction of a new class of auction mechanisms. Moreover, our bidder support tools are expected to make this complex trading mechanism more transparent to bidders, which may lead to higher acceptance of the mechanism thereby creating greater market liquidity.

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