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Effect of Information Feedback on Bidder Behavior in Continuous Combinatorial Auctions

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Combinatorial auctions—in which bidders can bid on combinations of goods—can increase the economic efficiency of a trade when goods have complementarities. Recent theoretical developments have lessened the computational complexity of these auctions, but the issue of cognitive complexity remains an unexplored barrier for the online marketplace. This study uses a data-driven approach to explore how bidders react to the complexity in such auctions using three experimental feedback treatments. Using cluster analyses of the bids and the clicks generated by bidders, we find three stable bidder strategies across the three treatments. Further, these strategies are robust for separate experiments using a different setup. We also benchmark the continuous auctions against an iterative form of combinatorial auction—the combinatorial clock auction. The enumeration of the bidding strategies across different types of feedback, along with the analysis of their economic implications, is offered to help practitioners design better combinatorial auction environments.

Key words: auctions; combinatorial auctions; information feedback; bidder behavior; experimental economics
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1. Introduction

Beginning with the Federal Communications Commission's (FCC's) announcement in October 1993 seeking proposals for conducting *combinatorial bidding* to sell electromagnetic spectra,[1] combinatorial auctions have received considerable academic attention (see de Vries and Vohra 2003 for a survey). Combinatorial auctions are multi-item auctions that allow bids on single items as well as on multiple items as a set, which is commonly referred to as a bundle or package. Compared to the sale of multiple items through separate single-item auctions, combinatorial auctions increase the allocative efficiency of trades when the values of the traded assets exhibit synergies that differ across bidders (Banks et al. 2003, Ledyard et al. 2002, Porter et al. 2003). Thus, the mechanism has been proposed for some prominent applications, including the allocation of airport time slots (Rassenti et al. 1982), spectrum rights (McAfee and McMillan 1996), rights to use railroad tracks (Brewer and Plott 1996), delivery routes (Caplice 1996), and the procurement of school meals (Epstein et al. 2002). In each case, the compelling motivation for the adoption of combinatorial auctions has been the presence of complementarity among assets (Cramton et al. 2006). For example, in the case of FCC spectrum auctions, AT&T may value licenses in two adjacent cities more than the sum of the individual license values, because AT&T's customers value roaming between the two cities. A combinatorial auction would allow AT&T to express its complex preferences.

However, the combinatorial auction mechanism has yet to become popular in the electronic marketplace, primarily because of the computational complexity of determining winners in such auctions and the cognitive complexity of formulating combinatorial bids (Porter et al. 2003). Several *iterative* solutions aimed at reducing the computational complexity have been introduced recently (e.g., Ausubel et al. 2005, Goeree and Holt 2010, Kwasnica et al. 2005). These approaches primarily focus on creating rules and restrictions to allow several well-defined rounds of bidding with the auctioneer declaring the intermediate results after each round. However, Adomavicius et al. (2007) have argued that in order for a combinatorial design to be feasible in the online marketplace, it is desired for a mechanism to be *continuous*[2]—in the

[1] Available at http://wireless.fcc.gov/auctions/general/releases/fc930455.pdf; last accessed October 20, 2011.

[2] A continuous combinatorial auction is similar to the open ascending format of single-item auctions (i.e., English auctions), where bids can be submitted at any time during the course of the auction;

sense that (i) it does not require an auctioneer's intervention, (ii) bidders can bid at any time, and (iii) bidders can join or leave freely during the auction. With the development of fast winner determination algorithms (Andersson et al. 2000, Fujishima et al. 1999, Sandholm et al. 2005, Tennenholtz 2000) and continuous bidder support schemes (Adomavicius and Gupta 2005, Adomavicius et al. 2007), implementing continuous combinatorial auctions has become a possibility. The design proposed by Adomavicius et al. (2007) allows bidders to join an auction at any time and make bids at any time (i.e., asynchronous bidding),[3] without an auctioneer's intervention or an activity rule. They demonstrated that with the aid of appropriate information feedback, continuous combinatorial auctions can generate high efficiency.

In this paper, we study how bidders behave in continuous combinatorial auctions. The study is motivated by the notion that in order to design effective information systems, it is essential to not only evaluate the performance of the systems but also analyze the interactions of the users with the systems that lead to certain economic outcomes (Bapna et al. 2003, 2004). Bapna et al. (2004, p. 1) assert that "users' preferences, behaviors, personalities, and ultimately their economic welfare are intricately linked to the design of information systems." For combinatorial auctions to be an effective online mechanism, it is important to understand the following questions: (i) What behaviors do bidders adopt in such auctions? (ii) How do features of the auction affect the behaviors? (iii) How do variations in bidding behavior affect the economic performance of the bidders?

Because combinatorial mechanisms in e-commerce are virtually nonexistent, a principal application of increasing our understanding of how bidders behave in these auctions relates to the design of novel combinatorial auction mechanisms. Whereas numerous studies have examined bidder behavior in various forms of single-item auctions (Bapna et al. 2003, 2004; Cox et al. 1982; Ockenfels and Roth 2006; Neugebauer and Selten 2006), only a few have attempted to analyze bidder behavior in combinatorial auctions (Brunner et al. 2010, Goeree and Holt 2010, Scheffel et al. 2011). Moreover, these studies examine bidder behavior in sealed-bid or iterative auctions. Our goal is to uncover the *actual* strategies pursued by bidders in *continuous* combinatorial auctions.

Because real data from combinatorial auctions are not publicly available, we rely on laboratory experiments for our empirical analysis. By investigating bidder behavior, the study aims to enhance the design of practical combinatorial auctions and also facilitate the design of more user-centric artificial bidding agents.

2. Background on Combinatorial Auctions

A combinatorial auction allows bidders to bid on combinations of items (i.e., item bundles) as well as on individual items. As a result, the number of biddable bundles increases exponentially with the number of items for sale, making the problem of determining winners[4] in such auctions NP-hard. With the rapid advances in computing and information processing power, determining winners for combinatorial auctions of practical sizes is no longer an issue in practice. The challenge faced by bidders in *formulating* combinatorial bids is a bigger practical problem (Adomavicius and Gupta 2005, Kwasnica et al. 2005). In single-item ascending auctions, it is easy to find out the provisional allocation, and hence easy to formulate a provisionally winning bid at any stage of the auction. However, in a combinatorial auction, computing the provisional allocation itself is an NP-hard problem. Furthermore, instead of two possible states (winning/losing) as in single-item auctions, bids in a combinatorial auction can have three possible states: (a) winning, (b) not currently winning but possibly winning in the future, or (c) losing (as detailed in the next section). Owing to these complexities, even if the winning set of bids is identified, formulating a provisionally winning bid on a chosen bundle can be cognitively challenging.

To lower the hurdles for bidders, several iterative designs have been introduced, each of which imposes certain restrictions to make the bidding environment simpler while generating high efficiency. Such designs include the combinatorial clock (CC) auction (Porter et al. 2003), clock-proxy auction (Ausubel et al. 2005), resource allocation design (RAD) (Kwasnica et al. 2005), and hierarchical package bidding (Goeree and Holt 2010). The primary focus of these studies has been the comparison of the economic properties of the mechanism—especially its efficiency—with that of existing designs. To the best of our knowledge, there does not exist a study of bidder strategies in combinatorial auctions that systematically looks at the

iterative auctions, on the other hand, proceed in a series of rounds, each of which last for a specified duration. In most iterative mechanisms, bidders cannot join the auction at any time because of activity rules that require bidders to satisfy certain criteria in the earlier rounds in order to bid in the later rounds.

[3] Lucking-Reiley (2000) suggests that one of the primary reasons behind the enormous popularity of online auctions is that they allow asynchronous bids; i.e., auction participants can submit bids any time during the course of the auction.

[4] The winners in combinatorial auctions are typically determined by computing the combination of bids that maximize seller's revenue with the assumption of cost-free disposal (Parkes 1999).

characteristics of the bids made by the bidders in such auctions and what impacts the different bidding patterns have on the outcomes of the auctions. Furthermore, although the iterative designs reduce the participation complexity of the bidders, they are difficult to deploy in the online marketplace because they do not allow asynchronous bidding.

Adomavicius et al. (2007) addressed this issue by developing several bidder support schemes to conduct continuous auctions, and demonstrating that high efficiency can be achieved by making the environment sufficiently transparent and user-friendly for bidders. These schemes (described in detail in §3) consist of *continuous*[5] information regarding provisional allocation and also *nonlinear* prices for all bundles of interest to the bidders. In this paper, we use this continuous mechanism to study bidder behavior in combinatorial auctions under three treatments that differ only in the quality of feedback provided to the bidders. Our objective is to learn how information feedback affects bidding behavior leading to differences in the retained surplus of bidders (i.e., the difference between the bidders' values and their winning bids, a common performance metric).

3. Characteristics of Combinatorial Auctions

3.1. Bid States in Combinatorial Auctions

In single-item ascending auctions (e.g., English auctions), if a bidder is not the highest bidder, she must bid an amount higher than the current highest bid to have a chance of winning the auction. However, in combinatorial auctions, even if a bid is not currently winning, it can still be among the future winners depending on the later bids. For example, in an auction of two items, P and Q, if the current bids are (1) \$2 for the single item {P}, (2) \$4 for the single item {Q}, and (3) \$8 for the package {PQ}, only the third bid is currently winning, assuming that the auctioneer's objective is to maximize his revenue. However, if a new bid of (4) \$7 for {Q} arrives, then bid 1, which was nonwinning after the first three bids, will now be among the winning bids because the combination of bids 1 and 4 (\$2 + \$7) is greater than the existing winning bid of \$8. Note, however, that after bid 4 has been placed, bid 2 can never win the auction because a higher bid (of \$7) has been placed on the exact same item.

Thus, at any given stage of a combinatorial auction, a bid can be in one of three possible states: (1) currently winning (*winning* state), e.g., the state of bid 3 following the first three bids; (2) currently nonwinning but with a possibility of winning in the future (*live* state), e.g., the states of bids 1 and 2 following the first three bids; and (3) currently nonwinning with no chance of winning in the future (*dead* state), e.g., the state of bid 2 following the first four bids. This is in contrast to traditional single-item auctions where a bid can only be in either of two possible states (winning or losing).

Reconsidering the auction stage following the first three bids in our exemplar two-item auction above, if a bidder chooses to place a minimal nonlosing bid on {Q}, she has a range of options available between $\$4+\varepsilon$ and $\$6+\varepsilon$, where ε is the minimum bid increment. If ε is \$1, a bid of \$7 on {Q} would make it *winning* at that auction stage along with bid 1, because $\$2+\$7 > \$8$ (where \$8 was the auction revenue after three bids), and a bid of \$5 or \$6 would make the bid *live*. We call the price (\$4) at or below which a bid will be *dead*, the *deadness level* (DL) and the price (\$6) above which a bid will be winning as the *winning level* (WL).[6] Furthermore, we represent the minimum price for a live bid (i.e., $\mathrm{DL}+\varepsilon$) as DL^*, and the minimum price for a provisional winning bid (i.e., $\mathrm{WL}+\varepsilon$) as WL^*. This exemplifies an important property of combinatorial auctions: there is not necessarily a single minimum successful bid as there is for single-item auctions. Instead, a minimal potentially successful bid can have a range of values.

Based on these characteristics of combinatorial auctions, the feedback schemes developed by Adomavicius et al. (2007) consist of, at every stage of the auction, (i) the provisional allocation, and (ii) DL^* and WL^* for any chosen bundle. The information feedback treatments (discussed in §4.3) that we use in our experiment are based on the manipulation of these schemes.

3.2. Combinatorial Clock Auction

To provide a benchmark for the continuous auctions, we conduct CC auctions. A CC auction is an iterative mechanism that was introduced by Porter et al. (2003) and has been used as a benchmark by Brunner et al. (2010) and Kagel et al. (2010). As a benchmark, this format has been used in multiple studies, and it is an efficient auction mechanism compared to most other notable iterative mechanisms, such as the simultaneous multi-round (SMR)[7] auction, Charles River

[5] Although some iterative mechanisms, such as the RAD and CC auctions, provide provisional allocation and price information to bidders as feedback, they do so only at the end of each round. In the continuous mechanism, the provisional allocation as well as the prices are updated after every bid.

[6] More details on winning and deadness levels and related theoretical results can be found in Adomavicius and Gupta (2005).

[7] SMR is a form of simultaneous ascending auction (SAA) that was used by the FCC for the allocation of the broadband spectra beginning in 1994. In the context of FCC auctions, the terms SAA and SMR have been somewhat interchangeably used. SMR does not allow package bidding.

and Associates (CRA) proposal,[8] RAD, and the simultaneous multiround auction with package bidding (SMRPB). In the study introducing the CC auction format, Porter et al. (2003) found it to be more efficient than both SMR and CRA. Brunner et al. (2010) found the CC mechanism to be more efficient than SMR and at least as efficient as RAD and SMRPB in environments with high asset complementarities. Kagel et al. (2010) found the CC mechanism to be more efficient than SMR.

A CC auction proceeds in discrete rounds, where bidders are allowed to submit package bids, only one of which could be provisionally winning in each round (i.e., XOR bids). In contrast, auctions like RAD allow OR bidding. A significant difference between a CC auction and other ascending combinatorial auctions is that in a CC auction, prices rise automatically and incrementally in response to excess demand. That is, whenever multiple bidders bid for the same item (either separately or as part of a package) in a round, the clock price for the item rises by the bid increment. Prices for items not having excess demand remain the same from one round to the next. Bidders observe the new prices at the end of each round and decide which packages to bid on. The prices of the packages are assumed to be the sum of the prices of the items constituting the packages and are therefore not exact (i.e., the prices do not necessarily reflect the minimum price required to win a given package at a given auction stage). Furthermore, the provisional winners and the new prices are revealed at the end of each round and do not continuously update after each bid.

4. Methodology

4.1. Experimental Environment

To study bidder behavior, we constructed a hypothetical combinatorial auction environment where bidders compete to acquire real-estate properties around a lake. The bidders can bid on individual lots as well as any combination of the lots. The valuation structure of the assets for each bidder is created in such a fashion that the bidders benefit by acquiring adjoining lots (because they afford more options for development) as a single bundle rather than separately. To test the robustness of the results concerning bidder behavior in continuous combinatorial auctions, we conducted two sets of experimental auctions with different setups. Setup 1 used a *symmetric, systematic* valuation scheme across bidders. Setup 2 used an *asymmetric, random* valuation scheme.

[8] The combinatorial auction design proposed by the consulting firm Charles River and Associates has been also referred to as the combinatorial multiround auction.

Figure 1(a) **Values of Individual Lots**

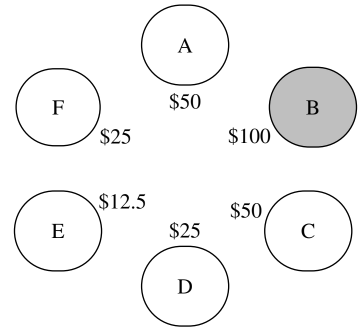
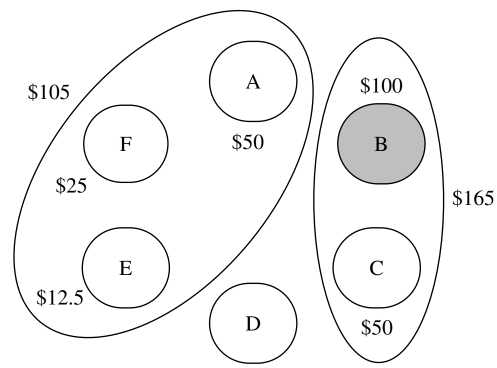


Figure 1(b) **Values of Combinations of Lots**



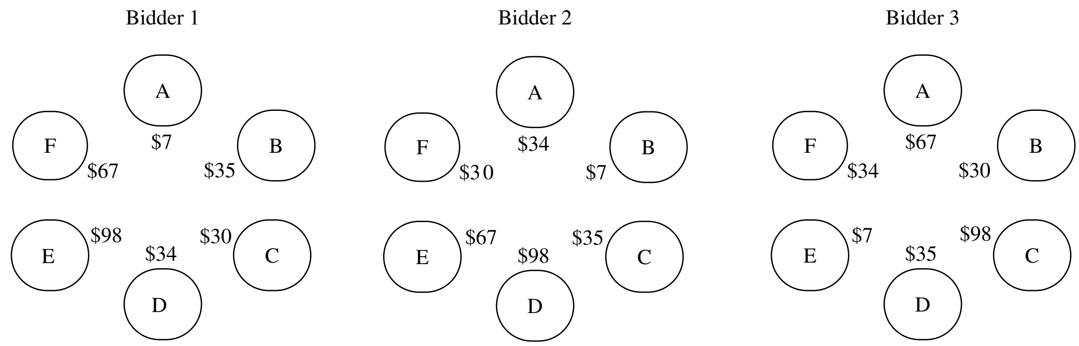
In setup 1, a distinct lot, designated the *preferred lot*, is identified for each bidder participating in the auction. This lot has the highest value for the bidder, with the value of the remaining lots decreasing by 50% as they are farther from the preferred position. An example of a possible individual-lot valuation structure is shown in Figure 1(a), where lot B (with a value of \$100) is shown as the preferred lot for some individual bidder.

In setup 2, the values of the lots for each auction are picked from a uniform distribution and then, for each bidder, randomly assigned to the lots. An example of a possible individual-lot valuation structure for setup 2 is shown in Figure 2, where the uniform distribution is [\$5, \$100].

In both setups 1 and 2, we introduce complementarities among lots by creating *superadditive* valuations for bundles with adjoining lots in them. This is accomplished by adding 10% to the additive valuation of the lots for each adjoining lot in the bundle. Thus, if the valuations of the individual lots are those depicted in Figure 1(a), then the valuation of the bundle {BC} with one adjoining lot is $(\$100 + \$50) * 1.1 = \$165.00$, and that of bundle {AEF} with two adjoining lots is $(\$50 + \$25 + \$12.50)*1.2 = \$105.00$, as shown in Figure 1(b).

This setup, similar to the experimental environment of Banks et al. (2003), allows both for a compact description of the scenario to the participants as

Figure 2 A Sample Assignment of Values in Setup 2



well as for building a simulation of the auction environment. We conducted several simulation runs with computerized bidding agents and several pilot tests with human bidders to refine the parameters of the model. For example, in setup 1, if the superadditivity rate is set at 25%, the optimal allocation is for one bidder to buy all the lots. In that case, if a bidder places a high bid on the bundle that includes all the lots, no other combination of bids can outbid her. After several simulations we chose to set the superadditivity rate to 10%,[9] this leaves ample room for combinations of packaged bids to outbid a single bid on all the lots. The same superadditivity rate was used in setup 2 to maintain consistency.

4.2. Rules and Procedure

To avoid confounding our results due to learning effects, we conducted a purely between-subjects study: Each subject participated in only one auction. We conducted three to four auctions simultaneously in each experimental session. Because the participants did not know how many auctions were being conducted, they did not know how many bidders they were competing against. The participants were all undergraduate business students (mean age 20 years; 54% male) who responded to volunteer solicitation announcements throughout the campus. Instructions explaining the rules of the auction were read aloud at the beginning of each session. The instructions were followed by short tests to familiarize the participants with the rules of the auction and the bidding environment. Subjects were randomly assigned to a particular auction. The auctions as well as the instructions were entirely computerized.

All auctions were conducted with six lots and three bidders. Whereas the rules to generate the valuations of the lots (i.e., the concepts of peak sites, decay and superadditivity rates) were common knowledge, the distribution of the values among the lots was private knowledge. Therefore, each bidder in an auction had no explicit knowledge of the specific lot valuations of other bidders. In setup 1, lots A, C, and E were designated as the preferred lots of the three bidders, respectively.

For both the continuous auctions as well as the CC auctions, a *soft* stopping rule was used; i.e., the auction continued as long as bids were being submitted. 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 practice of having a soft stopping rule is widely used in combinatorial auction research literature (Kwasnica et al. 2005, Brunner et al. 2010, Kagel et al. 2010).

The bidders were not given any fixed budget, but the final compensation scheme was a fixed amount of $10 plus an amount based on their individual performances in proportion to their surplus from the auction. Surplus was calculated as the difference between their valuation of the item(s) and their winning bid(s). Consequently, their surpluses were positive, zero, or negative depending on whether their winning bid was less than, equal to, or greater than their valuation, respectively. Those who failed to win any item only received the fixed amount of $10. Negative surpluses were taken off from $10, up to $10. At the end of a session, participants were paid privately in sealed envelopes.

4.3. Treatments and Interfaces for the Continuous Auctions

To observe how the variation of information feedback affects bidding behavior in continuous combinatorial auctions, we administer three treatments (with setup 1 as well as setup 2) that differ only in the amount of information available to bidders. The three treatments are (i) *baseline feedback* (BF), where all the bids are displayed anonymously to the bidders but no other feedback is provided; (ii) *outcome feedback* (OF), where, in addition to BF, the provisional winning allocation is identified at every stage of the auction; and (iii) *price feedback* (PF), where, in addition to OF, the two important minimum prices, DL* and WL*, are supplied on demand for any bundle of interest, in

[9] Brunner et al. (2010) consider a superaddivity rate of 20% as high and 1% as low.

order to aid bid formulation. It should be noted that BF can be provided in any combinatorial auction setting regardless of the winner determination approach. In addition, OF can be provided with most fast winner determination algorithms by solving the winner determination problem after each bid. PF can be provided in the continuous manner by the algorithm of Adomavicius and Gupta (2005), which we used in our experiments.

The bidders' assigned valuations for the individual lots were displayed on their screens at all times. The bidders could find their assigned valuations for any possible bundle by simply clicking on checkboxes corresponding to each of the six lots. For instance, if a bidder wanted to find her assigned value for the bundle {ABF}, she could click the checkboxes beside the lots A, B, and F, and the value would be displayed at the center of the screen. This provided an intuitive approach to user interface design, because the bidders could immediately view the valuations of bundles as they were composing them.

Bids could be placed by selecting the lots (i.e., composing the bundle), 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. With OF and PF, the set of winning bids was updated, if necessary, after every new bid. Furthermore, with PF, a bidder could find the two components of price feedback (DL^* and WL^*) by simply clicking on the lots constituting the bundle of interest. Finally, all dead bids, i.e., bids that stood no chance of winning at any subsequent state of the auction, were removed from display in the PF case. The subjects could refresh the screen by clicking either the checkboxes corresponding to the lots or a *refresh* button provided on the auction interface. Refreshing the screen updated the list of bids (in all treatments), the set of winning bids (in treatments OF and PF), and the minimum prices for a currently selected bundle (in PF only).

4.4. Interface for the CC Auctions

As in the continuous auctions, the bidders' assigned valuations for the individual lots were displayed on their screens at all times. The bidders could find their assigned valuations for any possible bundle by simply clicking on the checkboxes corresponding to each of the six lots. To place a bid, bidders needed to select the lots to compose the bundle, and then press the *submit bid* button. The current prices for all the lots were displayed on the screen. The prices for all the lots were set at \$5 at the start of the auction and increased by \$5 following the rules of CC auctions summarized earlier (§3.1). The prices were updated after every round. The bids submitted by a bidder both in the current round as well as in the previous rounds were displayed but the competitors' bids were not shown. If any of the bids was provisionally winning, it was highlighted. Note that provisional winners were announced by Kagel et al. (2010), but not by Brunner et al. (2010) or Porter et al. (2003). We chose to follow the format of Kagel et al. (2010) for a better comparison with the continuous auctions with feedback (outcome and price feedback treatments). Further, to maintain consistency with Kagel et al. (2010), we did not impose any activity rules restricting the items subjects could bid on. Whereas Porter et al. (2003) did not use activity limits either, Brunner et al. (2010) did.

4.5. Data Collection

We conducted a total of 94 continuous auctions: 51 using setup 1 and 43 using setup 2. All 282 (94×3) subjects in these auctions were unique participants, each of whom only participated in a single auction. The subjects used in the experiments with setup 2 were from a different university compared to those used with setup 1. We excluded 11 auctions from our analysis, because in these at least one bidder mistakenly placed a bid significantly above her valuation. They immediately notified us of the mistake; because our design disallowed bid withdrawal, rectification of the user error was not possible. Therefore, we removed these auctions from further analysis, attributing the irrational bids to bidding errors. The remaining auctions consisted of 44 auctions using setup 1 (14 with BF and 15 each with OF and PF) and 39 auctions using setup 2 (13 each with BF, OF, and PF). Over 3,000 bids were placed in each setup. In addition to the bids, to better understand the behavior of the bidders, the clickstream of each participant was also recorded. The clickstreams include data on the bidder's exploration of various bundles (the bidders' actions of checking and unchecking checkboxes on the display), screen refreshes, and bid submissions. About 50,000 clicks were recorded in each setup. Together the bids and clicks provide a rich data set for investigating bidders' behaviors. The bid data allow us to analyze patterns of participation of the bidders in the auction, and the clickstream data provide an opportunity to understand the bidders' underlying bid formulation processes.

In addition to the continuous auctions, we conducted 18 CC auctions to benchmark the performance of the continuous auctions. One auction had to be discarded for the same reason as stated above. The participants in these auctions were also unique and had not participated in the continuous auctions.

5. Results and Discussion

5.1. Efficiency Comparisons

Our main focus for this study is the data-driven exploration of the effect of feedback on the behaviors

Table 1 **Continuous Combinatorial Auctions in Setup 1 vs. Setup 2: Mean (SE) Efficiency**

	Baseline feedback (BF) (%)	Outcome feedback (OF) (%)	Price feedback (PF) (%)
Setup 1	86.23 (3.0)	90.64 (3.5)	93.48 (1.6)
Setup 2	78.78 (2.4)	86.74 (1.6)	89.39 (3.0)

of bidders. However, prior to presenting the analyses of the bidder behaviors, we provide several comparisons of the allocative efficiency of the continuous auctions. First, we compare the allocative efficiencies of the continuous auctions across the two experimental setups for consistency. Next, we use the iterative CC auction as a benchmark. Finally, we look at the allocative efficiency of two rational bidding strategies.

5.1.1. Allocative Efficiency of Two Continuous Auction Setups. Table 1 summarizes the allocative efficiencies for continuous combinatorial auctions. Also, the pairwise comparisons between treatments within each setup are presented below, where $\sim$ indicates no significant difference, $\succ^{*}$, $\succ^{**}$, and $\succ^{***}$ indicate significance at the 10%, 5%, and 1% levels respectively,

Setup 1: PF $\sim$ OF; OF $\succ^{*}$BF; PF $\succ^{**}$ BF;

Setup 2: PF $\sim$ OF; OF $\succ^{**}$BF; PF $\succ^{***}$ BF.

The pairwise comparisons indicate remarkable consistency between the two setups in terms of efficiency.

5.1.2. Allocative Efficiency of Combinatorial Clock Auction. Because the CC auctions were conducted with the symmetric and systematic bidder valuations, we compare the efficiency of the CC auctions to that of the continuous auctions in setup 1. The mean (SE) efficiency of the CC auctions is 90.4% (2.1%). Although the CC auction is more efficient (10% significance level) than the continuous auction with BF, its efficiency is not significantly different from that of the continuous auctions with feedback, either OF or PF.

5.1.3. Rational Bidding Strategies. Because assets in combinatorial auctions exhibit value synergies, the structure of the allocation problem is nonconvex, and therefore no equilibrium strategy may exist that can support the optimal allocation (Banks et al. 1989). In the absence of an equilibrium strategy, researchers have considered several feasible *rational* bidding strategies. The most popular among them is the *straightforward bidding strategy* (Ausubel and Milgrom 2002), wherein bidders in each round bid on the bundle(s) with the highest profit potential. This *myopic best response strategy* (Parkes 1999) has been considered as a rational bidding strategy in several studies (Bichler et al. 2009, Parkes and Unger 2000, Scheffel et al. 2011). However, Chen and Ledyard (2008, p. 10) point out, "There is no evidence that actual bidders will actually behave this way." This observation has been corroborated in laboratory experiments conducted by Kagel et al. (2010) and Scheffel et al. (2011).

Aside from straightforward bidding, another potential strategy that has been considered in the literature is a *powerSet bidding strategy* (Bichler et al. 2009), wherein a bidder places bids on not just the bundle with the highest profit potential but also on a few other bundles with high profit potentials, e.g., the 10 most profitable bundles in each round. However, unlike in iterative auctions that progress in discrete rounds, in continuous auctions it is impossible to clearly identify a powerSet strategy because other bidders may submit bids before a bidder completes bidding on the intended set.

To derive a benchmark for the observed bidding behaviors in our laboratory experiments, we ran auction simulations using these two strategies considered rational in the literature. In both our setups, straightforward bidding resulted in the convergence of all bids on the bundle that includes all the items, generating an efficiency of 78% in setup 1 and a mean efficiency of 78% (standard deviation of 4.7%) in setup 2, comparable to the efficiency observed in the baseline case. We provide further details of how closely the bidders in continuous auctions followed this strategy in §5.3, where we consider individual bidding behavior. With the powerSet bidding strategy, in setup 1, when bidders bid on their top five or more surplus generating bundles, 100% efficiency was achieved. In setup 2, because the distribution of values were not the same in each auction, depending on the instance, the 100% efficiency achieving powerSet varied from top three or more surplus generating bundles to top seven or more surplus generating bundles.

5.2. Overview of Behavior Analyses

Because observed behavior in a cognitively complex environment frequently deviates from theoretical predictions, our overall strategy for data analysis is to discover *meaningful* patterns from the data and interpret the patterns to provide insights regarding the different bidder strategies. At the outset, we identify three broad levels of analysis of the data that we have collected:

(i) We categorize overarching strategies of bidders through an analysis of the clickstream data and bidder-specific auction level data. Because the clickstream data represent the exploration that a bidder does before placing a bid, they capture aspects of the bid formulation process. Bidder-specific auction level data, such as the total number of bids made and the time of the first bid, capture characteristics of participation. Together, these data provide information about the bidders' strategies.

(ii) Next, we explore the relationship between bid types and bidder strategies. We characterize bid types using two different typologies. An understanding of bid properties helps to identify key characteristics that distinguish the bids placed within different strategies. We identify a mapping of bidder strategies over the bid characteristics to describe the complex temporal bidding process used in combinatorial auctions.

(iii) Finally, we conclude our analysis with an exploration of the economic implications of bidders' strategies, tying the data-driven analyses to the bidders' economic welfare.

Throughout these analyses, a major goal of this research is to examine the role that information feedback plays. If we understand the impact of different types of information on bidder behavior and auction dynamics, we can design practical mechanisms that achieve intended auction objectives, such as maximization of welfare, revenue, or market coverage. Therefore, we study the effects of feedback within each of the analyses.

5.3. Bidder Strategies

Our conceptualization of bidder strategies involves the activity that bidders engage in to formulate their bids and auction-level characteristics that capture the nature of participation by an individual bidder. To uncover the different bidder strategies, we conduct a cluster analysis based on four aggregate variables representing each bidder's behavior. The choice of the variables is in part based on existing literature on bidder behavior in a single-item setting (Bapna et al. 2003, 2004). However, because of the complexity of multi-item combinatorial auctions and our ability to collect primary data on bidder activity, we differentiate between bidder strategies (including bid formulation) and bid characteristics. In Bapna et al. (2004), bid characteristics are part of bidder strategies because bid formulation in single-item auctions is a rather straightforward process. But combinatorial auctions allow for the placement of several different types of bids. Therefore, we extend and adapt the input variables to our multi-item setting as well as on the availability of data that capture exploratory behavior by the bidders during the auction.

The variables considered by Bapna et al. (2004) were time of entry (TOE), number of bids (NOB), and time of exit (TOX). We consider TOE and NOB. TOX—the time of a bidder's final bid in the auction—is not pertinent in our setting because, instead of online auctions where bidders are free to join and leave any time over a period of a day or multiple days, our data come from auctions conducted in a laboratory, where bidders did not leave the auction until it was over and the average duration of the auctions was less than 30 minutes. In addition to TOE (called ENTRY in our setting) and NOB (called BIDS in our setting), we include two new variables: SPANS and EFFORT, which are particularly important in a multi-item setting. SPANS captures the number of distinct bundles that a particular bidder placed the bid on: e.g., if a bidder places bids only on bundles {ABC} and {AB}, then SPANS = 2. EFFORT captures the amount of exploratory analysis a bidder conducted before placing a bid, and is defined as the total number of clicks made by a bidder divided by the total number of bids placed by that bidder (i.e., the mean number of clicks per bid).

The means and standard errors for each of these dimensions in each treatment for the two setups are shown in Table 2. The mean of BIDS increases monotonically with the amount of feedback in both setups. It is interesting to note that EFFORT is highest with OF in both cases. With the availability of the winning set of bids at every stage of the auction (OF), the bidders could formulate better bids through greater effort. But in BF, without the provisional allocation or the prices, the bidders could not acquire meaningful information through greater effort. Further, with greater transparency (PF), the bidders did not need to expend as much effort to formulate efficient bids as they did in the other two cases. For instance, suppose that at a certain auction stage, the winning set of bids are {ABC} and {DEF} and the maximum bid on a bundle S is denoted by max $\{S\}$. If a bidder wants to bid on the bundle {BC}, she can bid max {ABC}—max $\{A\} + \varepsilon$ to be among the winning set replacing the bid on {ABC}, where ε is the bid increment. With BF, a lack of feedback regarding the currently winning

Table 2 Mean (SE) of Behavior Variables for Each Experimental Treatment in Both Setups

Feedback types (number of bidders)	BIDS	ENTRY [mm:ss]	SPANS	EFFORT
Setup 1				
Baseline feedback (BF) (42)	16.86 (13.51)	01:37 (02:59)	9.92 (6.59)	15.84 (14.31)
Outcome feedback (OF) (45)	24.98 (18.80)	02:38 (05:41)	11.80 (9.17)	24.85 (27.21)
Price feedback (PF) (45)	27.02 (15.19)	01:38 (03:10)	11.53 (5.79)	17.84 (11.51)
Setup 2				
Baseline feedback (BF) (39)	26.50 (15.57)	00:51 (01:36)	15.72 (7.52)	12.25 (13.53)
Outcome feedback (OF) (39)	36.18 (19.33)	00:46 (01:22)	17.87 (8.39)	13.08 (16.80)
Price feedback (PF) (39)	38.66 (17.45)	1:01 (02:61)	14.74 (6.54)	11.92 (9.42)

bids makes similar computation of potential winning bids difficult. But, with PF a bidder can easily find the exact current winning price on {BC} (in this example) without needing to explore suitable complementary bids.

To uncover differences in bidder behavior as captured by the four input variables, we used the k-Means clustering algorithm in conjunction with the expectation-maximization (EM) algorithm to determine the value of k, i.e., the optimum number of clusters in each case (Witten and Frank 2005). This well-known clustering mechanism has been used for similar analysis (e.g., Bapna et al. 2004).

The clustering algorithm uncovered three groups of bidders in each treatment. The cluster means (centroids), arranged in ascending order of BIDS within each type of feedback, are shown in Table 3. Comparing the three clusters across feedback types, we find that the properties of each cluster are very similar across treatments. The small number of bidders in the first cluster in each type places the fewest bids over the fewest spans, but invests a massive amount of effort in placing them. Based on their aggregate bidding behavior, it appears that these bidders carefully analyze the bid space before narrowing down the set of spans and placing a small number of bids; therefore, we call the bidders in the first cluster *analyzers*.

In all three treatments, the second cluster is characterized by moderate activity—both in terms of the number of bids and spans, as well as the number of clicks per bid. This class of bidders usually starts bidding within the first minute of the start of the auction (ENTRY $\leq$ 1:00, except with OF in setup 2). Because the bidders in this cluster seem to place bids in regular intervals throughout the auction and exhibit qualitatively similar behavior as attributed to *participators* in single-item auctions by Bapna et al. (2004), we call the bidders in the second cluster *participators* as well.

In all three treatments, the bidders in the third cluster are characterized by a larger number of bids on significantly more spans than bidders in the other two clusters. These bidders put comparatively the least amount of effort in placing their bids. Thus, it appears that the bidders in this cluster explore the bid space by placing a large number of bids after only a rudimentary analysis. Based on these observations, we label the bidders in the third cluster as *explorers*.

One notable difference between the clusters in the two setups is the greater number of analyzers in setup 2 for all the treatments. Although the percentage of explorers is not much different, the percentage of analyzers is greater and that of participators is lesser in setup 2 compared to those in setup 1. One possible explanation for the difference is that the asymmetric and random valuation structure of setup 2 posed a bigger challenge to bidders for placing profitable bids. Compared to setup 2, it was relatively easier for bidders to bid in setup 1, wherein they could focus on and around their preferred lots. However, the same level of focused strategy was not possible for the analyzers in setup 2. As a consequence the analyzers placed more bids and on relatively more spans as compared to their counterparts in setup 1. In setup 2 analyzers also entered earlier and spent less bidding effort. Overall, although the analyzers still spent more effort and are more

Table 3 Cluster Centroids for Bidder Classes

Feedback types	Clusters (number of bidders)	BIDS	ENTRY [mm:ss]	SPANS	EFFORT
Setup 1					
Baseline feedback (BF)	Analyzers (2)	2.00	14:15	1.50	66.00
	Participators (34)	13.41	01:00	8.38	14.23
	Explorers (6)	41.33	00:43	21.50	2.43
Outcome feedback (OF)	Analyzers (1)	18.00	10:05	2.00	144.78
	Participators (36)	18.72	02:18	8.67	25.32
	Explorers (8)	54.00	03:10	27.13	7.70
Price feedback (PF)	Analyzers (4)	15.50	11:05	8.00	32.97
	Participators (34)	23.06	00:43	9.88	17.45
	Explorers (7)	52.86	00:35	21.57	11.15
Setup 2					
Baseline feedback (BF)	Analyzers (13)	10.62	01:00	8.15	16.80
	Participators (18)	28.67	00:35	18.56	10.49
	Explorers (8)	47.60	01:18	25.20	6.81
Outcome feedback (OF)	Analyzers (11)	10.64	00:35	6.45	26.23
	Participators (21)	37.00	01:26	19.14	8.61
	Explorers (7)	73.85	00:26	32.00	5.83
Price feedback (PF)	Analyzers (11)	15.45	1:18	10.27	20.96
	Participators (20)	34.00	00:35	15.90	8.73
	Explorers (8)	83.60	02:10	30.20	7.63

Table 4 Percentage of Bids That Were Best Response

	Setup 1				Setup 2			
	Analyzers	Participators	Explorers	Total	Analyzers	Participators	Explorers	Total
Baseline feedback (BF)	0.0	7.5	4.8	6.5	9.4	6.9	4.2	6.3
Outcome feedback (OF)	16.7	10.7	3.7	8.0	9.4	8.1	2.7	6.2
Price feedback (PF)	19.3	21.7	13.2	19.0	19.4	11.7	11.9	12.7

focused than the participators, in setup 2 the difference between analyzers and participators is not as stark as it is in setup 1. Thus, the relative proportions of analyzers and participators are likely influenced by the relative difficulty of the bidding task and the dispersion in valuation distribution of the items in a bundle.

In terms of how closely these three types of bidders followed the best response strategy discussed earlier, the behavior we observe (summarized in Table 4) is no different from what has been observed in previous studies (Kagel et al. 2010, Scheffel et al. 2011); i.e., bidders do not consistently follow a best response strategy. This suggests that identification of profit maximizing bundles (along with their prices) is a potential feedback that could be provided to bidders to assist them in their bid formulation, however, such feedback would require the bidders to disclose their valuations on an exponential number of bundles.

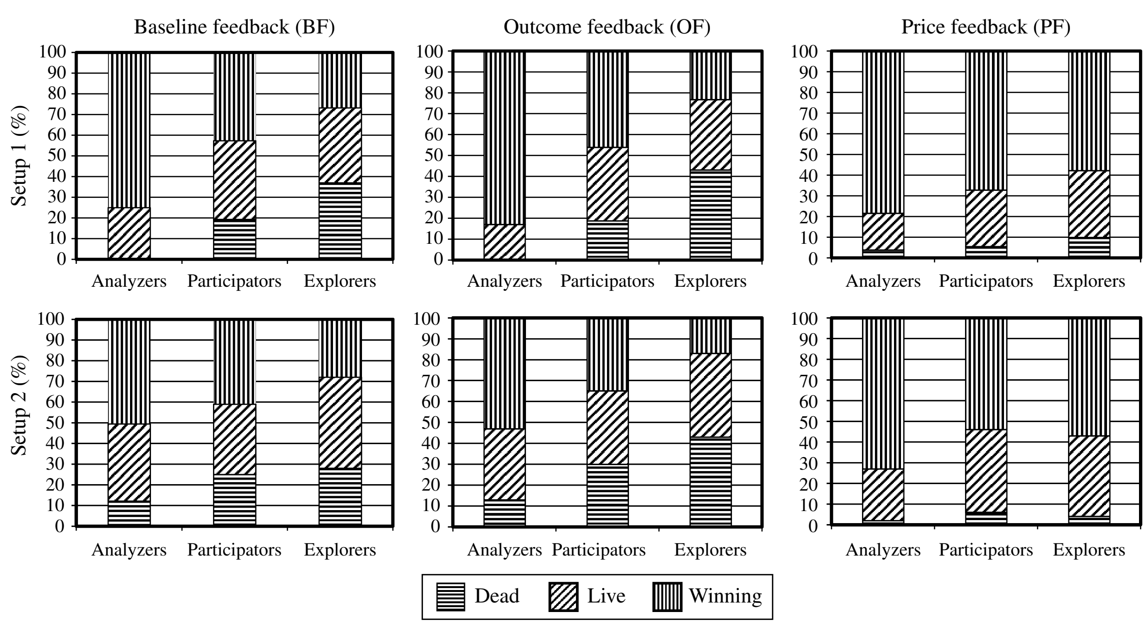
Overall though, the analyses of bidder strategies demonstrate a remarkable consistency across the two setups, given the quite different experimental conditions. The systematic nature and limited number of primary bidding strategies is a significant finding and contribution of this study. To delve into more specific understanding of these strategies, in the next three subsections we develop an analysis of bid characteristics that we relate to these strategies.

5.4. Analyses of Individual Bids: Bid States

We first explore a basic characterization of bids, i.e., the bid state (dead, live, or winning) at the time they are placed by the bidders. Our interest in exploring the bid states across different bidder strategies stems from a desire to learn the effectiveness of the strategies in leading to successful bids under the different information regimes (BF, OF, and PF). We address the questions: (i) What proportion of live and winning bids do bidders place? (ii) Do bidders place a large percentage of dead bids with BF and OF, where the minimum prices to place live and winning bids are not identified? (iii) Are certain bidders more capable than others in identifying the minimum prices even without explicit feedback?

The percentages of dead, live, and winning bids that each type of bidders placed are shown in Figure 3. One can think of the ratio of winning and live bids to dead bids as a measure of the success or effectiveness of a bidding strategy as well as the helpfulness of the information feedback provided to the bidders, because dead bids represent lost effort. Three

Figure 3 Mix of Bids Placed by the Different Types of Bidders



trends stand out from the figure. The first is the significantly higher proportion of winning bids placed by the analyzers across feedback conditions as compared to both participators and explorers. In addition, the analyzers (who spent the highest amount of effort in placing each bid) also placed the fewest percentage of dead bids overall. Interestingly, in setup 1, even with just BF and OF, analyzers do not place dead bids. The fact that this class of bidders places a few dead bids with PF might seem surprising, but the likely cause of this behavior is that the DL* can increase (by virtue of other bids) between the time a bidder observes this level and the time she places a bid. We show later that with PF the bidders place bids that are extremely close to DL* and WL*; hence, the likelihood that these marginal bids can be outbid when additional bids are placed, is quite high. We study this phenomenon in more detail in §5.5. Analyzers placed some dead bids in all three treatments in setup 2. The number of dead bids is still small for analyzers across all conditions.

The second major pattern in the figure is the similarity of bid state distributions across the three types of bidders in the baseline and outcome feedback conditions, with increasing proportions of winning bids (and smaller proportions of dead bids) from explorers to participators to analyzers. The analyzers are the most effective bidders with very few dead bids, whereas the explorers, who place a large number of bids with minimal effort, appear to be the most ineffective, making a large percentage of dead bids. Although the explorers were actively bidding throughout the auction, they were not actively analyzing the existing bids before placing a bid and ended up placing a large percentage of inconsequential bids.

The similarity of bid states with BF and OF raises the question of whether the addition of only the provisional allocation feedback helps the bidders in estimating the prices of the bundles. At the outset, only the analyzers appear to be able to estimate the prices and place profitable bids even without the availability of PF. We will further explore this in the next section, where we refine the bid characterization to explore the impact of feedback at a much finer granularity.

Without the aid of exact prices to make a potentially live or winning bid, the percentages of dead bids with BF and OF across all bidder strategies are almost identical: 30% with BF and 31% with OF in setup 1 and 42% with BF and 43% with OF in setup 2. Even the percentages of live and winning bids are fairly close with these two types of feedback: 38% live and 32% winning with BF, and 32% live and 37% winning with OF in setup 1, and 33% live and 25% winning with BF and 30% live and 27% winning with OF in setup 2. Thus, without feedback regarding potentially live and winning bids, on average the mix of bids is similar with BF and OF. However, there is one important difference between the two: with OF, identifying the winning bids provided an implicit WL for the few bundles included in the winning set. Thus, whereas only about 30% of the bids placed on currently nonwinning spans (i.e., bundles that were not part of provisionally winning allocation) in either setup were winning bids, about 75% of the bids placed on the winning spans (bundles that constituted the provisional allocation at that state of the auction) were winning bids. This implicit identification of bundles with known WL also explains the slightly higher percentage of winning bids with OF as compared to that with BF.

The third pattern in the figure is the similarity in bid state distributions for all the three bidder strategies with price feedback. The availability of PF had a big impact on the distribution of bid states. The effectiveness of both the participators and explorers moves toward that of the analyzers. This phenomenon demonstrates the value of PF for the bidders in combinatorial auctions. It also emphasizes the fact that bidder behavior can be significantly influenced by the design choices made by an auctioneer. With PF, far fewer dead bids overall (about 6% compared to about 30% in each of the other two treatments in setup 1 and about 40% in each of the other two treatments in setup 2) were placed and a far greater proportion of winning bids (65% compared to about 35% in the other two treatments in setup 1 and 59% compared to about 25% in the other two treatments in setup 2) were placed. The decrease in dead bids is expected because of the availability of exact bundle prices, but the high percentage of winning bids with PF implies that, with the availability of provisional allocation and exact prices for any chosen bundle (i.e., information analogous to that automatically available in single-item ascending auctions), the dynamics of the combinatorial auctions become similar to English auctions, where every new bid is a winning bid. In spite of the relatively higher percentage of winning bids with price feedback, the winning bids with the PF were closer to the prescribed minimum (WL*). On average, with bidders not explicitly aware of the WL*, the winning bids with OF were about \$25 above the WL* compared to only about \$10 above the WL* with PF in either setup.

In summary, the types of feedback and individual differences in bidders' strategies have a consistent effect on the states of the bids that are placed. We find that in either setup, availability of price feedback leads to fewer dead bids, as expected, but also to a high percentage of winning bids. Further, just announcing the provisional winners (OF) does not change the behavior of the bidders significantly, in so far as the bid states are concerned. However, price feedback changes their behavior considerably.

5.5. Taxonomy of Bid Characteristics

Although the mapping of bid states across different bidder strategies provides some interesting insights, in this subsection we develop a more refined taxonomy. The taxonomy includes more nuanced characteristics that identify, for example, whether the bid is barely live (i.e., just above DL) or is quite close to WL, or whether the bid was placed early in the auction or late. The more complex characterization of bids will allow us to better understand the bidding dynamics. The resulting taxonomy of bids is then related to bidder strategies and feedback in §5.6.

The taxonomy is developed empirically by conducting cluster analysis on the bids in each treatment based on the following attributes of each bid: (i) TIME—the normalized time when the bid was placed; e.g., if a bid was placed halfway through the auction, the TIME is 0.5. (ii) SIZE—the size of the bundle on which the bid was placed, in terms of the number of items in the bundle; e.g., the SIZE of a bid on {ACD} is 3. (iii) STATE—the state of the bid immediately after it was placed, defined as -1 if the bid was *dead*; 0 if it was *live*; and 1 if it was *winning*. (iv) WINSPAN—defined as 1 if the bundle on which the bid was placed was among the provisional winners right before the bid was placed, and 0 if it was not winning. (v) EXCESS_DL—the percentage by which the amount of the bid was above the DL*, i.e., the minimum required to place a *live* bid, calculated as (Bid-DL*)/DL* for a bid above the DL*, and 0 otherwise. (vi) EXCESS_WL—the percentage by which the amount of the bid was above the WL*, i.e., the minimum required to place a *winning* bid, calculated as (Bid-WL*)/WL* for a bid above the WL*, and 0 otherwise. (vii) SEARCH—the total number of *clicks* by the bidder prior to placing the bid.

Note that with PF, the winning bids were continuously identified at each stage of the auctions, and the minimum potentially winning bids could be immediately obtained by the bidder for any chosen bundle. Furthermore, all the dead bids were removed from display. Thus, STATE, WINSPAN, EXCESS_DL, and EXCESS_WL were directly available to the bidders. With OF, WINSPAN was known because the winning set of bids was identified, but STATE, EXCESS_DL, and EXCESS_WL were only available indirectly and in a very limited sense—only for the (very few) bids that were provisionally winning at a given time. For instance, if a bid of $100 on bundle {ABC} is winning at a certain stage of the auction, $100 is the DL as well as the WL on {ABC}, according to the theoretical results derived in Adomavicius and Gupta (2005). Thus, the identification of winning bids implicitly provided feedback regarding the minimum potential bids on those bundles. However, at any stage of the six-item auction, there could only be between one and six winning bundles out of the 63 possible bundles. With BF, none of this bid-related information (i.e., STATE, WINSPAN, EXCESS_DL, and EXCESS_WL) was explicitly provided to the bidders.

As in the bidder analysis, we use the EM algorithm (Witten and Frank 2005) to find out the optimum number of bid clusters, and then apply the k-Means procedure to discover the clusters. We find five clusters with BF, six with OF, and four with PF. The cluster centroids are shown in Table 5. Although the number of clusters discovered in each treatment differs, significant similarities exist in the clusters across the three treatments, allowing us to identify six bid types overall.

For each feedback condition, we find a cluster with *jump bids* (with high EXCESS_DL and high EXCESS_WL) placed early in the auctions. These bids are all winning bids (STATE $=1$) in setup 2 and with PF in setup 1 but a mix of live and winning bids with BF and OF in setup 1; furthermore, they occur after moderate to high SEARCH. We call these bids *early aggressive winning bids* (EAWB).

With BF and OF we find a cluster of *early dead bids* (EDB): dead bids (STATE $= -1$) placed relatively early (TIME < 0.40) in the auctions. Similarly, we find a cluster of *late dead bids* (LDB) characterized by primarily dead bids placed relatively late in the auctions (TIME > 0.65). We do not find either of these clusters with PF.

Another bid type in the first part of the auctions is a cluster of *early live bids* (ELB), seen in each treatment except with BF in setup 1, containing primarily live bids placed relatively early in the auctions (TIME < 0.35). These bids are somewhat similar to the earlier occurring EAWB, but occur a little later and are less aggressive (i.e., have smaller EXCESS_DL and EXCESS_WL values).

Along with the continued use of dead bids (LDB defined above) with BF and OF, in the second half of the auctions the bids retain a similar character with a somewhat more conservative slant compared to the first half. In all three treatments, we find a cluster of bids placed on provisionally winning bundles (WINSPAN $= 1$). With both BF and OF this cluster contains about 15% of the bids in that treatment and is entirely composed of winning bids (STATE $= 1$). With PF it contains 19% of the bids in setup 1 and 24% in setup 2, with over 90% winning in each case. Based on these characteristics, we call this cluster of bids *winning span winning bids* (WSWB). The bids bear a similarity to the initial EAWB; however, they are less aggressive with lower EXCESS_DL and EXCESS_WL. For BF and PF, these bids involve slightly less SEARCH than is used for EAWB; but for OF, a high amount of SEARCH is required.

Table 5 Cluster Centroids for Bids

Feedback type (no. of bids)	Clusters (% of bids)	TIME	SIZE	STATE	WINSPAN	EXCESS_DL	EXCESS_WL	SEARCH
Setup 1								
Baseline feedback (BF) (708)	(EAWB) (29%)	0.17	2.09	0.41	0	28.91	10.74	13.15
	(EDB) (20%)	0.38	2.74	−1	0.1	0	0	7.3
	(ELB)[a]							
	(WSWB) (14%)	0.53	2.84	1	1	0.11	0.11	10.49
	(LDB) (10%)	0.68	4.83	−0.99	0.07	0	0	11.08
	(CLWB) (27%)[b]	0.69	2.59	0.23	0	3.17	0.38	12.91
Outcome feedback (OF) (1,124)	(EAWB) (21%)	0.20	1.85	0.53	0	20.34	7.85	17.09
	(EDB) (15%)	0.36	2.36	−1	0.21	0	0	8.10
	(ELB) (13%)	0.25	3.77	0.21	0	13.21	3.86	17.34
	(WSWB) (14%)	0.61	2.60	1	1	0.07	0.07	26.81
	(LDB) (16%)	0.67	3.92	−1	0	0	0	14.52
	(CLWB) (20%)	0.72	2.78	0.44	0	2.40	0.02	21.46
Price feedback (PF) (1,216)	(EAWB) (23%)	0.22	2.49	1	0	6.18	4.30	15.64
	(ELB) (27%)	0.33	2.37	−0.20	0	3.13	0	12.04
	(WSWB) (19%)	0.53	2.41	0.94	1	0.40	0.40	13.00
	(CLWB) (31%)	0.78	2.87	0.79	0	0.92	0.03	19.34
Setup 2								
Baseline feedback (BF) (1,023)	(EAWB) (14%)	0.27	2.32	1	0	14.90	7.94	12.40
	(EDB) (23%)	0.33	3.42	−1	0	−0.35	−0.50	9.25
	(ELB) (22%)[a]	0.30	1.68	0	0	6.83	−0.53	9.30
	(WSWB) (15%)	0.52	3.13	0.56	1	0.03	0.03	11.14
	(LDB) (27%)	0.78	3.01	−0.59	0	−0.12	−0.47	10.27
	(CLWB)[b]							
Outcome feedback (OF) (1,411)	(EAWB) (27%)	0.29	3.01	1	0	14.41	9.43	10.94
	(EDB) (13%)	0.29	4.83	−0.98	0.02	−0.20	−0.29	6.45
	(ELB) (13%)	0.17	2.34	−0.42	0.07	6.67	−0.43	6.90
	(WSWB) (14%)	0.48	3.21	1	1	0.07	0.07	8.98
	(LDB) (17%)	0.70	2.69	−1	0.08	−0.29	−0.49	5.79
	(CLWB) (16%)	0.66	2.60	0.04	0	2.27	−0.03	7.46
Price feedback (PF) (1,510)	(EAWB) (28%)	0.45	2.14	1	0	5.21	2.28	8.59
	(ELB) (28%)	0.32	2.25	−0.18	0	4.45	−0.46	9.18
	(WSWB) (24%)	0.47	3.55	0.86	1	0.05	0.05	9.69
	(CLWB) (20%)	0.77	1.87	0.49	0	0.52	−0.20	11.80

[a]This cluster exists in setup 2 but not in setup 1.
[b]This cluster exists in setup 1 but not in setup 2.

Finally, in all three treatments (with the exception of BF in setup 2) we find a cluster of live and winning bids placed relatively closer to the DL and WL. Thus we call these bids *conservative live and winning bids* (CLWB). These bids bear a similarity to the ELB but are placed much later in the auction and are generally more conservative, with lower EXCESS_DL and EXCESS_WL.[10] Further, these bids are associated with a higher amount of SEARCH compared to the ELB.

Overall, we find the clusters in the two setups to be very similar, with two notable differences, both with BF: The cluster of CLWB is found in setup 1 only, and the cluster of ELB is found in setup 2 only. Comparison of the clusters with BF in the two setups reveals that the EDB cluster appeared in setup 2 primarily at the expense of the EAWB, which were 29% in setup 1 but only 14% in setup 2. It could be that the bidders wanted to place winning bids but, because of the relatively more challenging environment in setup 2, ended up placing bids that were live but not winning. This is also most likely the reason that in setup 2 it was harder to place live or winning bids toward the end of the auction with BF. This resulted in the LDB cluster that is almost triple the size (in term of percentage) in setup 2 as it is in setup 1 while the CLWB cluster vanished. Thus, the increased difficulty of the task with the less structured valuations led to less effective bidding when no outcome or price feedback was provided. The provision of this feedback improved the performance so that this increased task difficulty was mitigated and lowered bid effectiveness (resulting in substantially more dead bids) was not observed.

In summary, like in the case of bidders (§5.3), we find a fairly stable taxonomy of bids in each treatment.

[10] For PF in setup 1, EXCESS_WL is not lower for CLWB because of a floor effect. In other words, for ELB with this feedback, EXCESS_WL is already at its minimum (i.e., 0). The value for CLWB is not appreciably higher (0.03).

The analysis reveals that, unlike assumptions of rational bidding, actual bidders place a variety of bid types and not just one. In the next section, we explore the patterns of bid type usage by different bidder strategies.

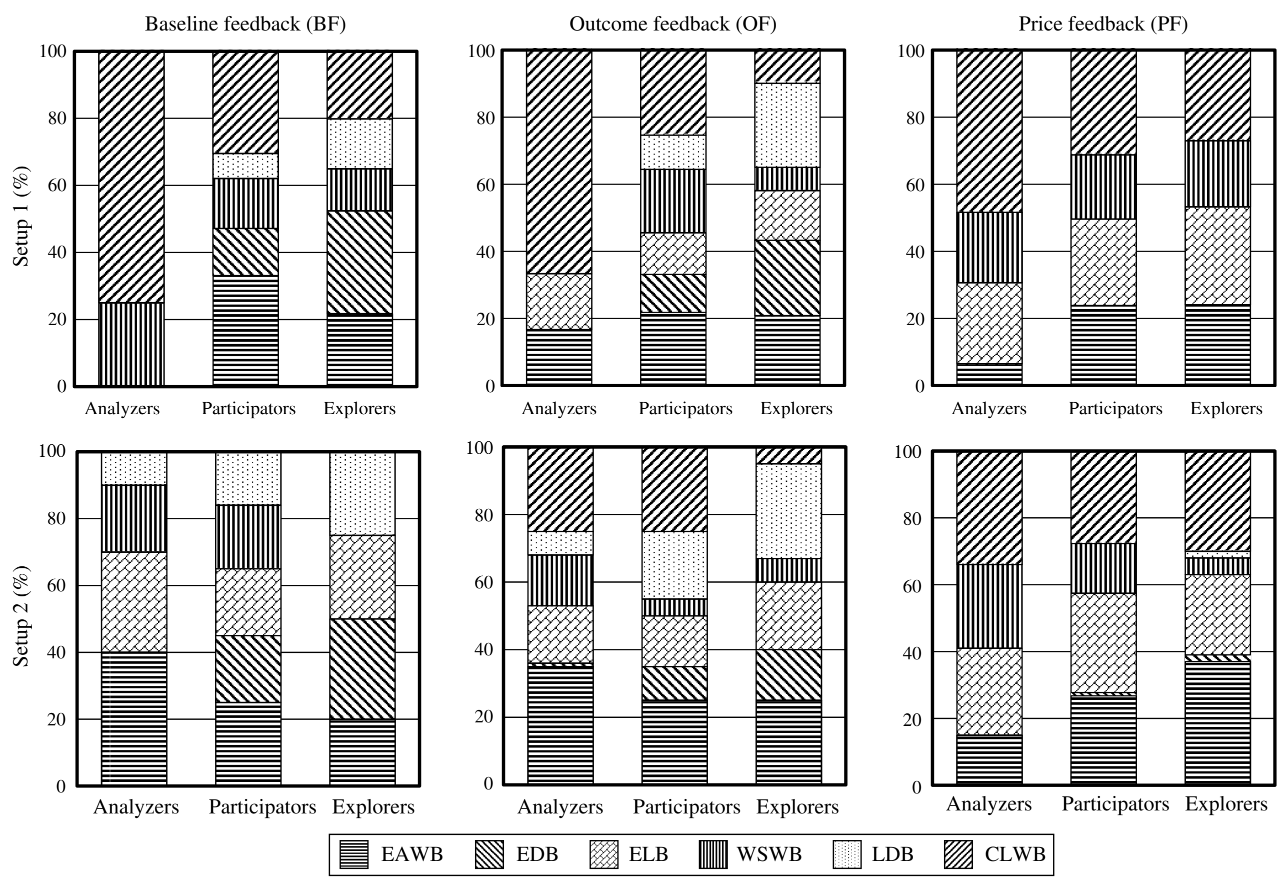
5.6. Bidder Strategies and Bid Characteristics

The considerable consistency in the bid clusters across the three feedback conditions with the fine-grained level of individual bids validates their use as a sound taxonomy to help develop a better understanding of bidder behavior. In this section, we use this bid taxonomy along with the classifications of the bidders (identified in §5.3) to explore the types of bids that different classes of bidders place under different types of feedback.

Figure 4 graphically displays the percentages of bid types by types of bidder and feedback for the two setups. Several bidding tendencies are apparent from the charts. First, in §5.4, we noted that participators and especially explorers place a large number of dead bids with BF and OF. The detailed analysis confirms the result but provides some interesting additional insights. It is clear from Figure 4 that explorers place significantly higher number of dead bids than participators. Further, although analyzers do not place any dead bids in setup 1, a significantly larger number of analyzers in setup 2 results in a few late dead bids. However, except for analyzers who only place late dead bids in setup 2, there is no consistent pattern in terms of whether the dead bids are placed early in the auctions (EDB) or late in the auctions (LDB). So, even with a small number of bids early in the auctions, the participators and explorers found it hard to realize with BF and OF that the bids they are placing are below DL*; on the other hand, analyzers seem to be able to avoid early dead bids. Also, a reduction of dead bids does not occur as learning during the auction. The reduction primarily arises with appropriate feedback (PF) or with a particular bidding strategy (analyzer's strategy).

Second, another difference is tied to bidding strategy: In setup 1, analyzers place a significantly higher proportion of conservative live and winning bids (CLWB) as compared to other bidders and as compared to the other type of bids they themselves place. Three-fourths of the analyzers' bids with BF, two-thirds with OF, and close to half with PF are CLWB. These bids are a prime component of the analyzer strategy in setup 1. Note that CLWB is likely to result in highest surplus, especially with conservative live bids. However, in setup 2, CLWB is a dominant

Figure 4 Bid Composition for Each Bidder Type



strategy only with PF, and the strategy does not even appear with BF. It appears that with the more complex valuation structure (with setup 2), price feedback (PF) is necessary for even analyzers to use this higher surplus generating strategy.

Third, as the information content of the feedback increases, the number of early aggressive winning bids (EAWB) changes in interesting ways. In both setups, participators place more aggressive early bids in BF and OF as compared to explorers; however, with PF participators place fewer aggressive bids as compared to explorers, especially with setup 2. This effect is even more pronounced for analyzers in setup 2 where they place the highest number of EAWB bids with BF and OF but the smallest number of EAWB with PF. It appears that bidders that conduct a higher level of analysis before placing a bid tend to bid less aggressively early as more feedback is provided, whereas the bidders that conduct less analysis either do not change the aggressiveness of their early bids or even increase their aggressiveness as more feedback becomes available. This seems to be a defining difference between analyzers and the other bidder types.

Fourth, analyzers and participators seem to be the most consistent users of *winning span winning bids* (WSWB). It is part of the participators' strategy in every treatment, and of the analyzers' strategy in virtually every treatment (except for OF in setup 1). Explorers, on the other hand, seem to be using this strategy sparingly.

Finally, with both setups, the tendency to place ELB increases from OF to PF. The availability of prices appear to positively influence the tendency to place live bids early in the auction, however, the bidding strategy does not appear to have any impact on the use of ELBs. Thus, differences in the use of ELBs is driven by the situation and not by the strategy used by the bidder. Between OF and PF, feedback aids in the placing of live, but not necessarily winning, bids early in the auction. With BF, the behavior is not so clear: there are no ELB in setup 1 but a significant number of them in setup 2. Although this needs to be further examined in the future, we believe the higher number of ELB in setup 2 is consistent with the higher number of LDB in that setup both of which arise out of the use of more conservative bidding in setup 2, most likely due to a more challenging valuation structure.

An understanding of how bidding strategies differ across different types of bidders and which of these strategies are more susceptible to changes in valuations and which are more robust against these changes help understand the effect of design choices on bidder strategies. Toward that end, it should be noted that bidder strategy distributions are quite similar across the two experimental setups for PF as opposed to BF and OF where there is a much larger variance in the distribution of strategies employed by the bidders. In the next subsection, we explore the economic impact of bidding strategies employed by the bidders.

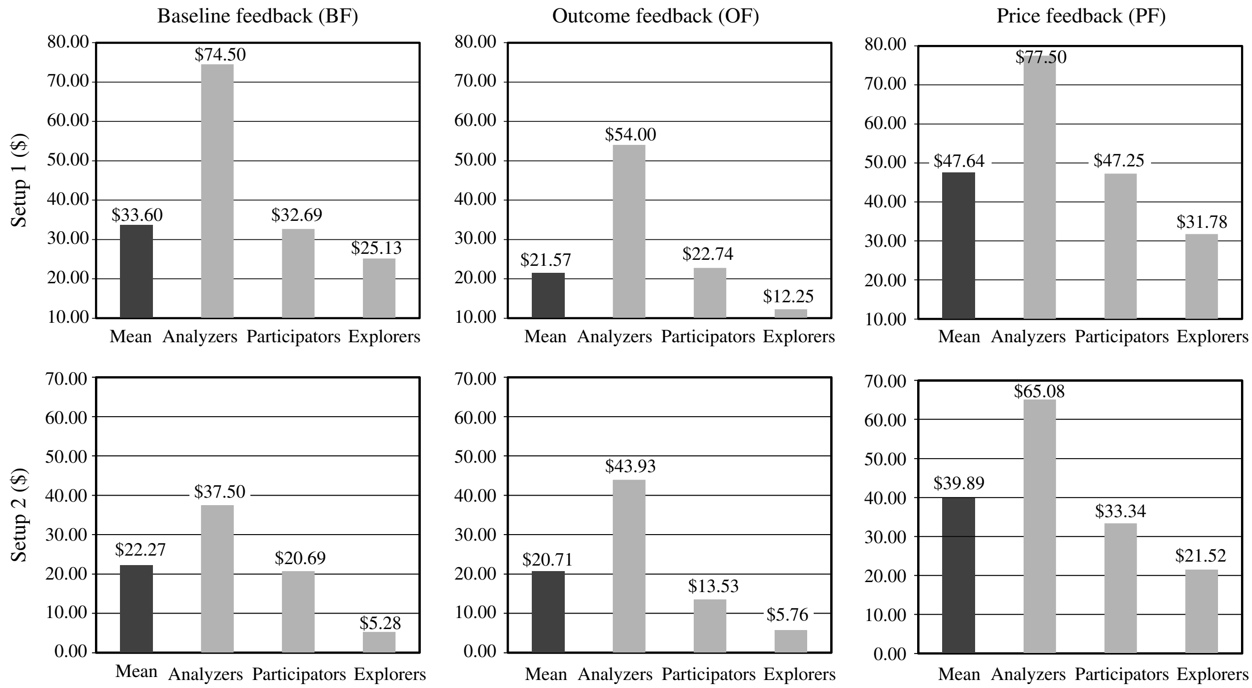
5.7. Impact of Bidder Strategies on Bidders' Economic Welfare

An important consideration in the design of trading mechanisms is the profit implications of different bidding strategies (Bapna et al. 2004). Having a reasonably good understanding of the structural nature of bids placed by the bidders, we conclude our results with attention to the success of the three classes of bidders, as individuals, in generating surplus for themselves. In particular, we want to learn whether the analyzers, with their seemingly superior bidding strategy, are able to garner higher surplus than their counterparts. We also observe how different combinations of bidders, as a group, impact the surplus.

The mean surplus drawn by each type of bidder in each treatment is shown in Figure 5. Within each type of feedback, the analyzers generate the maximum surplus for themselves, whereas the explorers retain the minimum surplus. Feedback type also influences surplus, with OF decreasing the surplus and PF increasing the surplus, compared to the baseline case.

In addition to these individual-level patterns upon surplus, we are also interested in auction-level bidder patterns. In particular, because an auction is a competitive game, we hypothesize that the types of the other bidders, with which each bidder had to compete, will have an effect on economic outcomes, including the retained surplus. Out of the 10 possible combinations of three bidder types (because each auction had three bidders), four different combinations of bidder types were present in the auctions that we conducted with setup 1: {APP} ($n=7$), {PPP} ($n=22$), {PPE} ($n=9$), and {PEE} ($n=6$), where A represents analyzer, P represents participator, and E represents explorer; and nine combinations were present with setup 2: {AAA} ($n=2$), {AAP} ($n=5$), {AAE} ($n=3$), {APP} ($n=5$), {AEE} ($n=3$), {PPP} ($n=10$), {PPE} ($n=3$), {PEE} ($n=3$), and {APE} ($n=5$). Thus, for a given bidder, the possible combinations of competing bidders were {AP} ($n=14$), {PP} ($n=82$), {PE} ($n=30$), and {EE} ($n=6$) in setup 1, and {AA} ($n=14$), {AP} ($n=25$), {AE} ($n=17$), {PP} ($n=38$), {PE} ($n=17$), and {EE} ($n=6$) in setup 2. We call these combinations of competing bidders *competition types* and, based on our analyses above, we characterize them as follows: {AA}—*highly intense*, {AP}—*intense*, {AE} and {PP}—*strong*, {PE}—*moderate*, and {EE}—*weak*. As can be observed from the combinations presented above, in setup 1, no bidder faced highly intense competition.

Figure 5 Average Surplus Generated by Each Bidder Type



For the individual's retained surplus, we use ANOVA to study the three factor model including feedback effect, the effect of the bidder's own type (in terms of the three bidder strategies), the competition type effect, and all possible interactions. The results for both setups are shown in Table 6. Overall, the model is significant at the 1% level with a reasonably good explanation of variance (adjusted $R^2 > 17\%$). As observed in Figure 5, the bidder strategies have a significant impact on bidder's surplus. Interestingly, although in Figure 5 feedback appears to have a direct impact on surplus, feedback and competition have no direct effect. Instead, the two factors interact in their relationship to surplus. The impact of bidder strategies is also moderated by competition; i.e., the effectiveness of a strategy is dependent upon the other bidders in the auction.

Table 6 ANOVA of the Factors Influencing Individual's Surplus

	Setup 1		Setup 2	
	Degrees of freedom	F	Degrees of freedom	F
Feedback type	2	2.13	2	1.81
Bidder type	2	3.26^{**}	2	2.95^{*}
Competition type	3	0.56	4	1.23
Feedback type × Bidder type	4	0.24	4	0.33
Feedback type × Competition type	6	2.83^{**}	8	2.20^{**}
Bidder type × Competition type	1[a]	4.58^{**}	7	3.96^{***}
	$R^2 = 0.3036$; Adj. $R^2 = 0.1927$; $F(18, 113) = 2.74^{***}$		$R^2 = 0.3659$; Adj. $R^2 = 0.1735$; $F(27, 89) = 3.10^{***}$	

[a]The degree of freedom is only 1 for lack of data points for all possible combinations of bidder and competition types.

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

To uncover the patterns of these interactions, we employ pairwise t-tests. Table 7 presents the results from pairwise comparisons of the surplus by feedback and competition types (with N/A indicating where comparisons could not be conducted because of lack of data) for the two setups.

It is quite clear that with PF, bidders generally extract greater surplus as compared to that with BF and OF under most of the competitive environments. This is primarily because bidders with PF were able to formulate more precise bids due to the availability of information regarding the minimum prices required to place live and winning bids. The bidders with OF, on the other hand, could find out whether they were winning, but not how much to bid on a bundle of their choice to place provisionally winning bids. Thus the nonwinning bidders placed large bids in order to become winners. For instance, if we consider the late *jump* bids (bids well above WL* in the final quarter of auctions) with OF, more than 75% of those bids in either setup were placed by the bidders who were not winning at that point. Without the feedback on minimum prices, these bidders placed jump bids, thereby squeezing their surplus. Thus, except in one case (with intense competition in setup 2), the retained surplus of bidders with OF was either similar

Table 7 Tests of the Effects of Feedback on Surplus Within Each Type of Competition

	Highly intense (AA)	Intense (AP)	Strong (PP & AE)[a]	Moderate (PE)	Weak (EE)
Setup1					
Outcome vs. baseline feedback	N/A	$t\ (4) = 1.707$	$t\ (56) = 2.76^{**}$ (BF > OF)	$t\ (16) = 0.499$	$t\ (3) = 2.00$
Price vs. baseline feedback	N/A	$t\ (10) = 2.577^{**}$ (PF > BF)	$t\ (50) = 0.48$	$t\ (18) = 2.38^{**}$ (PF > BF)	N/A
Price vs. outcome feedback	N/A	$t\ (8) = 3.457^{**}$ (PF > OF)	$t\ (52) = 1.84^{*}$ (PF > OF)	$t\ (20) = 2.27^{**}$ (PF > OF)	N/A
Setup2					
Outcome vs. baseline feedback	$t\ (9) = 1.45$	$t\ (13) = 1.98^{*}$ OF > BF	$t\ (33) = 1.89^{*}$ BF > OF	$t\ (8) = 2.31^{**}$ BF > OF	$t\ (2) = 1.89$
Price vs. baseline feedback	$t\ (7) = 1.66$	$t\ (19) = 2.17^{**}$ PF > BF	$t\ (34) = 2.06^{**}$ PF > BF	$t\ (10) = 1.83^{*}$ PF > BF	$t\ (1) = 2.11$
Price vs. outcome feedback	$t\ (6) = 2.16^{*}$ PF > OF	$t\ (13) = 1.84^{*}$ PF > OF	$t\ (37) = 3.21^{**}$ PF > OF	$t\ (9) = 0.72$	$t\ (3) = 1.33$

[a]No instance of {AE} in setup 1.
** and * denote statistical significance at the 5% and 10% levels, respectively.

to or significantly less than that of their counterparts with BF.

This analysis, important for system designers, validates the observation in behavioral research that simply providing *outcome* feedback is generally insufficient for decision makers to make myopically optimal decisions (e.g., Brehmer 1980). Because OF lacked strategic information regarding which lots and amounts to bid, this type of feedback was unable to help the bidders in making profitable decisions.

Besides feedback, competition also has a moderating effect on the impact of bidder strategies. Table 8 presents the detailed comparisons via pairwise *t*-tests to further investigate the nature of this moderation. In setup 1, we had insufficient observations for analysis for the intense and weak competition types, and even for the moderate competition type we could conduct only one comparison (the others indicated as N/A). For the groups in setup 2 and for the groups with sufficient data to conduct the analysis in setup 1, the general pattern observed in Figure 5 is statistically validated. Analyzers obtained the highest surplus, participators were next, and explorers had the lowest surplus. The added nuance is that competition reduces the difference between participators and explorers. Participators extract higher surplus with moderate competition, but not with strong competition in setup 1. Even in setup 2, explorers generate higher surplus than participators with weak competition, and are only weakly dominated by participators with highly intense and strong competition. An in-depth analysis of the competition's moderating effect

Table 8 Tests of the Effects of Bidders on Surplus with Different Types of Competition

	Highly intense (AA)	Intense (AP)	Strong (PP & AE)[a]	Moderate (PE)	Weak (EE)
Setup1					
Analyzers vs. participators	N/A	N/A	$t\ (71) = 3.60^{***}$ (A > P)	N/A	N/A
Analyzers vs. explorers	N/A	N/A	$t\ (14) = 2.06^{**}$ (A > E)	N/A	N/A
Participators vs. explorers	N/A	N/A	$t\ (73) = 0.63$	$t(28) = 4.07^{***}$ (P > E)	N/A
Setup2					
Analyzers vs. participators	$t\ (9) = 2.63^{**}$ A > P	$t\ (18) = 2.31^{**}$ A > P	$t\ (44) = 1.72^{*}$ A > P	$t\ (9) = 2.55^{**}$ P > A	$t\ (4) = 0.81$
Analyzers vs. explorers	$t\ (7) = 3.21^{**}$ A > E	$t\ (13) = 2.09^{*}$ A > E	$t\ (18) = 1.84^{*}$ A > E	$t\ (9) = 0.84$	$t\ (1) = 2.10$
Participators vs. explorers	$t\ (6) = 1.96^{*}$ P > E	$t\ (13) = 0.56$ P > E	$t\ (41) = 2.01^{*}$ P > E	$t\ (10) = 2.95^{**}$ E > P	$t\ (3) = 2.39^{*}$

[a]No instance of {AE} in setup 1.
***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

on the impact of bidder strategies across all possible competition types constitutes an interesting direction for future work.

In summary, we find that analyzers retained the highest surplus followed by the participators and explorers. The analyzers were able to effectively use the available information to actively navigate the search space and place bids with higher precision. Their adaptive strategy, along with consistent use of CLWB and avoidance of dead bids, allows them to be successful even with the changes across setups. The explorers, on the opposite end of the strategy spectrum, did not attempt to effectively use the available information, placed a large percentage of inconsequential (dead) bids, both early and late in the auction, and as a result ended up with a lower average surplus.

6. Conclusions

When assets have value complementarities that differ across bidders, combinatorial auctions can have significant advantages over multiple single-item auctions of the assets. To study the behavior of bidders under different conditions, we constructed an experimental combinatorial bidding environment. Unlike other combinatorial auction mechanisms proposed in the literature, the mechanism used for this study is continuous. However, with proper information provided to the bidders, the design remains as efficient as the CC auction, which has been shown to be an efficient iterative mechanism in multiple studies.

Although studies of bidder behavior in single-item auctions (Bapna et al. 2003, 2004) focused primarily on bidding behavior, our analysis added the clickstream data of bidders that allowed us to better understand the bidders' decision-making processes. Our analysis applied these data to detail both the types of bidders and the types of bids placed by them. The analysis of the bid and click data revealed three bidder types—analyzers, participators, and explorers—each exhibiting a distinct set of bidding behaviors that is consistent across different information feedback regimes and valuation schemes. This stable taxonomy of three bidder types based on their aggregate bidding behavior is a major finding of our research. Some bidders, with more profitable bidding strategies than others, are able to generate higher surpluses than their counterparts. Furthermore, the type of competition (in terms of bidding strategies) that a bidder faces in an auction moderates the effect of feedback on the retained surplus. In addition, we identified six distinct types of bids that bidders placed in the auctions. The three types of bidders differed in the portfolio of their bids. Further, the strategies were sensitive to the information provided, with the increased transparency of price feedback reducing the heterogeneity in the type of bids placed.

Stepping back from the details of the findings, the main managerial contributions are threefold. The primary contribution is the understanding of bidder behavior in these continuous auctions. To design an effective combinatorial auction mechanism that could be deployed in the online marketplace with a high probability of success, it is important to understand how the manipulation of design parameters (such as the information feedback provided to bidders) influences their bidding behavior, and how certain behaviors of agents lead to differing economic outcomes. To date, researchers have focused on developing fast algorithms and heuristics to accelerate winner determination as well as on designing iterative mechanisms to simplify participation. Still, despite their potential relevance, these auction mechanisms have not penetrated the consumer marketplace. The development of practical continuous designs of combinatorial auctions that maintain intuitive features of popular English auctions is believed necessary for general use of combinatorial auctions among consumers. The technical developments for conducting continuous combinatorial auctions are now available, but the study of bidder behavior in such auctions has been largely untouched. The manner in which users interact with information systems is crucial to their design (Bapna et al. 2004). Following this insight, the present study provides an important, valuable, and necessary step in developing the underpinnings for combinatorial auctions to be feasible for general consumer use. Because continuous combinatorial auctions are not yet a popular mechanism in practice, we do not have field data to study the type of bids made in such auctions. The findings from this research can be used in simulating realistic continuous combinatorial bidding environments. Conceptually, the endeavor is similar to that of Leyton-Brown et al. (2000) who created the combinatorial auction test suite (CATS) of distributions for generating combinatorial bids in five application domains based on assumptions of how bidders might construct bundles and bid amounts. This software has been frequently used (Adomavicius and Gupta 2005, Gunluk et al. 2005, Hudson and Sandholm 2004, Sandholm et al. 2005, Yokoo et al. 2001) to evaluate and optimize combinatorial auction winner determination algorithms. Our study, by throwing light on how human bidders place bids in a competitive environment, provides insights for generating more realistic bid distributions for the study of continuous combinatorial auctions. We believe that studies regarding the performance of combinatorial auctions (Adomavicius et al. 2007, Goeree and Holt 2010, Kwasnica et al. 2005) combined with an understanding of bidder behavior in such auctions will enable the design of continuous combinatorial auction environments that can be deployed in the online marketplace with a high probability of success.

Thus, the knowledge of bidder types based on their bidding characteristics provides the tools for auction simulations, and allows for a more focused investigation of different strategies and their implications. With this knowledge, researchers will be able to simulate different bidder types and observe human bidder behavior when engaged with simulated bidders of different types.

A second managerial implication concerns how bidders handle complexity as a component of combinatorial auctions. Although computational complexity is no longer an issue, because of recent advances, the cognitive complexity from the bidders' standpoint still requires investigation. The auctions' complexity primarily arises from three sources. The first is the degree of competition, a factor whose investigation is initiated in this study as varying between the two continuous auction setups. The other two sources of complexity are the number of items being sold in the auction and the number of bidders participating in the auction. Future research needs to expand our understanding of the effects of complexity along these different dimensions.

The third broad managerial implication concerns the role of feedback, particularly as a way of handling complexity in continuous combinatorial auctions. Our examination of the impact of feedback suggests that the dynamics of combinatorial auctions can be significantly influenced by strategically manipulating the information provided to the participants. Owing to the complexity of the package bidding environment, bidders can benefit from continuous feedback that assists them in understanding the state of the auction in terms of what bids are winning and how much the bidders need to bid to place a winning bid. Our analysis of the bid characteristics suggests that, without price feedback, bidders are still unable to formulate effective bids, resulting in a large percentage (30% to 40%) of dead bids (i.e., inconsequential bids). With feedback on exact prices and provisional allocation, bidders are able to place bids with greater precision. As a result, we believe that providing price feedback is likely to be essential for the sustainability of the mechanism in the online marketplace. Otherwise, the cognitive complexity and unprofitability in terms of surplus will lead to nonparticipation by bidders.

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