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USER HETEROGENEITY AND ITS IMPACT ON ELECTRONIC AUCTION MARKET DESIGN: AN EMPIRICAL EXPLORATION[1]

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Abstract

While traditional information systems research emphasizes understanding of end users from perspectives such as cognitive fit and technology acceptance, it fails to consider the economic dimensions of their interactions with a system. When viewed as economic agents who participate in electronic markets, it is easy to see that users' preferences, behaviors, personalities, and ultimately their economic welfare are intricately linked to the design *of information systems. We use a data-driven, inductive approach to develop a taxonomy of bidding behavior in online auctions. Our analysis indicates significant heterogeneity exists in the user base of these representative electronic markets. Using online auction data from 1999 and 2000, we find a stable taxonomy of bidder behavior containing five types of bidding strategies. Bidders pursue different bidding strategies that, in aggregate, realize different winning likelihoods and consumer surplus. We find that technological evolution has an impact on bidders'*

[1]Ron Weber was the accepting senior editor for this paper.

strategies. We demonstrate how the taxonomy of bidder behavior can be used to enhance the design of some types of information systems. These enhancements include developing user-centric bidding agents, inferring bidders' underlying valuations to facilitate real-time auction calibration, and creating low-risk computational platforms for decision making.

Keywords: Electronic markets, online auctions, bidding strategies, user behavior taxonomy, smart agents, valuation discovery, calibration, simulation

Introduction

Using information technology as a key ingredient, electronic markets match globally dispersed buyers and sellers, facilitate transactions, and provide the necessary regulatory institutional infrastructure (Bakos 1998). Electronic markets can also be characterized as *economic information systems*. Consequently, we argue their design has to incorporate the economic dimensions of users' interactions with the system. In this paper, we use business-to-consumer (B2C) online auctions as a representative electronic market and adopt a data-driven, inductive approach for developing a taxonomy of bidder behavior. Bidders pursue different bidding strategies that realize different chances of winning and different levels of consumer surplus. We demonstrate how the taxonomy of bidder behavior can be used to enhance the design of economic information systems. This includes developing user-centric bidding agents, inferring bidders' underlying valuations to facilitate real-time auction calibration, and creating low-risk computational platforms for decision making.

Our objective is to show how individuals use economic information systems in different ways. This is particularly apparent in the instance of online auctions because the outcomes map directly to users' pockets. Nonetheless, the necessity of considering the economic impact of an information system's design is being recognized across a broad range of applications. For instance, Ba et al. (2001) illustrate the importance of considering the *interests and incentives* of users in such areas as distributed decision support systems, knowledge management, and e-business supply-chain coordination.

This study contributes to the literature by addressing the following three research questions:

(1) Is there a systematic way of characterizing bidding strategies in online auctions?

(2) How do different bidding strategies affect bidders' economic welfare? Do certain strategies lead to higher economic rents than others?

(3) How can the findings from these two questions be used to enhance the design of online auctions?

Overall, we find a stable taxonomy of bidder behavior containing five types of bidding strategies. Differences among the strategies are defined by (1) bidders' decisions about entering and exiting the mechanism and (2) their number of bids. Because these factors also coincide with the price formation process, we show how our taxonomy can be used to design the next generation of online auctions using dynamic mechanism-design principles. The taxonomy assists in developing smart, user-centric bidding agents and with drawing statistical inferences about bidders' valuations as an auction progresses. An auctioneer can take advantage of these inferences to perform real-time calibration of auctions by changing mechanism-design parameters such as bid increments. Understanding the taxonomy of bidders' behaviors is also useful in creating computational simulation platforms. These can be used to conduct risk-free, decision theoretic analysis of online auctions.

The paper proceeds as follows. First, we briefly review the auction format discussed in this paper—namely, the multiunit online Yankee auction. In the next section, we develop our bidder taxonomy by presenting a conceptual model and providing a theoretical basis for the strategic variables selected. We then discuss the data and present the classification methodology. Next, we report the results of the classification and analyze the economic welfare of the identified strategies and the likelihood each has of winning. In the same section, we discuss these implications from a longitudinal perspective and briefly touch upon user-learning effects. We conclude by discussing three specific applications of our findings.

The Yankee Auction

In a Yankee auction, there are *multiple identical units* for auction, and each auction specifies minimum starting bids and bid increments. Bidders may purchase more than one unit, but they all must be purchased at the same price. Bidders desiring more than one unit are required to make lumpy bids (Tenorio 1999). With lumpy bids, bidders demand several units at the same price. They are not permitted to specify a demand schedule, detailing how many units they are willing to buy at a certain price. For example, a bidder wanting five units in a Yankee auction that started at $40 and had a $20 bid increment is not permitted to bid $100 for three and $80 for two items at the same time.[2] Therefore, demand reduction, which can occur when bidders are allowed to present a demand curve (Ausubel 2002; Lucking-Reiley 1999), is not an issue. Bidding takes place progressively until a predetermined time period expires. All winning bidders pay their own prices. Ties are broken first by price, second by quantity, and third by time. For example, suppose two bidders are competing for four available units. One bids $10 for three units, while the other bids $10 for one. If a new bidder bids $12 for one unit, that bidder becomes the highest winning bidder and leaves three units for lower-priced bidders. The bidder at $10 for three will remain a winning bidder because of greater quantity. The bidder at $10 for one will be bumped from the highest bidder list. If both had bid for two units, the bidder with the earliest initial bid would remain a winner.

A Yankee auction terminates on or after[3] a pre-announced closing time, and winning bidders pay the amount they last bid to win the auction. In multiunit settings, this rule often leads to bidders paying different amounts for the same item. The soft closing time provides a disincentive to last-minute bidding and is designed to attract bids early in the auction. Successful Yankee auctions on the Internet include Ubid.com and Onsale.com.

Conceptual Model

Here we focus on developing an empirically driven taxonomy of bidder behavior in online auctions. A robust taxonomy can then be used to perform *ex post* theory building, shedding light on what drives real online bidders to make their bidding decisions. We do not begin with a theory and then attempt to prove or disprove it. Rather, we begin with an area of interest (in our case, the largely ignored aspects of bidder behavior). Relevant insights are allowed to emerge. We have a strong reason for employing this research strategy. Auction design has been the focus of significant theoretical (for a review, see McAfee and McMillan 1987; Milgrom 1989; Myerson 1981; Rothkopf and Harstad 1944) and experimental attention (for a review, see Kagel and Roth 1995). It has even been the subject of some limited empirical work (Laffont et al. 1995; Paarsch 1992). However, *most research focuses on the bid-taker's perspective and assumes a certain bidder behavior*. In the traditional closed, face-to-face auction setting, it was reasonable to assume that bidders belonged to a homogenous, symmetric, risk-neutral group who adopted Bayesian-Nash equilibrium strategies.[4] While tenable in the context of face-

[2]Auction sites such as Ubid and Onsale require credit-card-based name-and-address verification of bidders. This requirement exists primarily to prevent shill bidding, but it also effectively constrains full demand schedule specification.

[3]Most auctions have a "going, going, gone" period such that the auction terminates after the closing time has passed and no further bids are received in the last five minutes.

[4]Bayesian games are games of incomplete information in which each agent knows her own payoff function but at least one agent exists who is uncertain about another

to-face, single-item auctions, this set of assumptions quickly breaks down with most multiunit online auctions (Bapna et al. 2003a). It is well known that the computation of equilibrium bidding strategies is intractable in these auctions (Nautz and Wolfsetter 1997).

In addition, the existing literature is outside the Internet environment. Significant structural changes resulting from the online environment challenge some of the existing theory's core assumptions. The most salient of these, tracing its origin to the fundamental requirement of pursuing a classical game-theoretic analysis, is the *ex ante*, exogenously known number of bidders. However, this assumption is readily violated in online auctions. For example, recent analysis with eBay data reveals that bidder entry is influenced endogenously by the hidden reserve price adopted by the sellers (Bajari and Hortascu 2001).

Our adoption of an inductive approach to developing a bidder taxonomy challenges the notion that one can build a theory by assuming a single bidder type. Our reasoning is consistent with Engelbrecht-Wiggans' (2000) suggestion that

> There is a lot to be learned from trying to understand why real bidders do the things that they do. When actual behavior differs from that predicted by the theory, it is all too easy to dismiss the actual bidders as being simple. Instead, we should ask if it is the theory that is being simple.

With this quote in mind, we investigate whether heterogeneity exists in bidder behavior in online auctions. Given the longstanding assumption of homogenous, rational, strategic bidders, this investigation represents a new way of thinking. It is important to note that we are not seeking to derive an *ex ante* explanatory model of heterogeneous user behavior in online auctions. Instead, we focus on understanding different bidding behaviors to help further the design of online auctions.

player's payoff function. In the context of a Bayesian game, a Bayesian-Nash equilibrium is one in which each player's course of action is a best response to the other players' strategies.

Model Description

Using several theoretically motivated parameters, we developed a model for exploring user heterogeneity (Figure 1). If heterogeneity in bidding behavior indeed exists, it is worthwhile to analyze the impact of the different strategies on the likelihood of winning and on consumer surplus. We also evaluate longitudinal shifts in bidding behavior.

The vertical parentheses around the bidder strategy properties box are used to indicate the *ex ante* unknown number of bidding strategies.[5] Taken together, the dotted, downward arrow and box represent the fact that after we observe empirical regularities in bidding strategies, we hope to explain some of them based on factors such as bidding cost, exogenous signals, and endogenous design choices.

Identification of Strategic Variables: Theoretical Considerations

Our initial challenge was to identify *observable* classification variables that could be collected by an unbiased, automated agent. The variables had to have a *sound theoretical basis* in the auction's price formation process. In addition, we wanted to work with variables that could *subsequently be used to influence* the economic welfare of the agents (auctioneer and/or bidders) by implementing mechanism-design changes. Therefore, we were not interested in measuring intrinsic bidder attributes like risk profile that could not be altered by modifying the mechanism.

[5] This is based on the cardinality notation in mathematics.

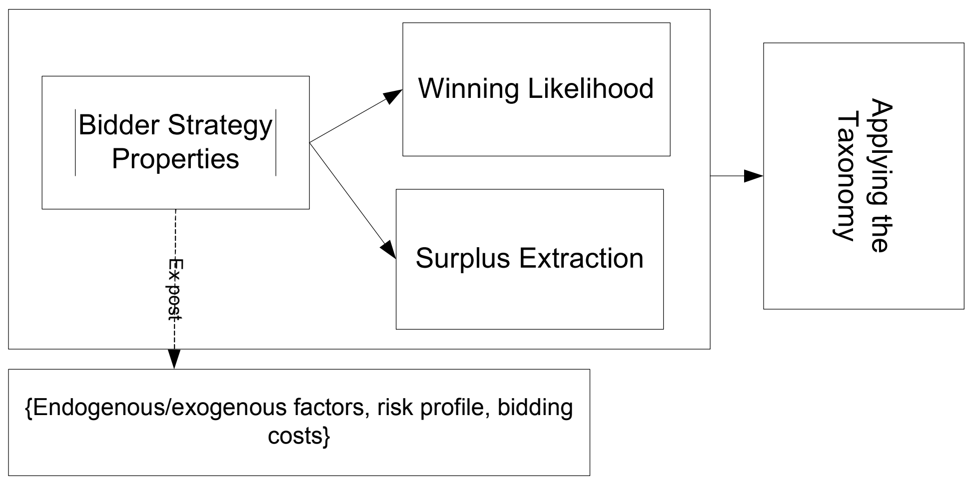

Figure 1. Conceptual Model: A Taxonomy of Bidder Behavior and Resulting Consequences

We chose three strategic variables—time of entry, time of exit, and number of bids—and then carried out a multi-attribute bidder classification procedure.

Time of Entry (TOE)

The time at which a bidder chooses to enter the auction directly influences the auction's participation level and its price-formation process. Not surprisingly, Klemperer (2000) argues that attracting entry is a pillar of good auction design. TOE is treated as a *variable* in this study, which is a departure from most auction-theory literature. It is necessary, however, in the context of a globally dispersed, online user base. Auction-theory literature typically takes the number of bidders as exogenously given (Laffont et al. 1995; Paarsch 1992).[6] Engelbrecht-Wiggans (1987) found that the auctioneer realized higher expected revenue by choosing a reserve price that led to a larger number of bidders. In contrast, Harstad (1990) points out that a seller often benefits more from an auction with fewer participants because, given common values, fewer participants implies a higher chance of winning. Thus, each bidder may settle for lower expected profit. Levin and Smith (1994) also claim that the presence of too many bidders hurts welfare because of higher coordination costs.

The TOE variable captures the bidder's normalized auction entry time. Our automated data collection agent can monitor this variable. Thus, it is not subject to biases that might arise in survey-collected data. In addition, it can be influenced by the endogenous mechanism-design rules chosen by auctioneers (Bajari and Hortascu 2001; Engelbrechtt-Wiggans 1987). Depending on the auction mechanism design, TOE could indicate the strategic value of a bidder's response. For instance, we have seen that late entry is strategic in single-unit auctions with hard closing times, such as those on eBay (Roth and Ockenfels 2002). On the other hand, if the time priority of a bid is used as a bid preference order mechanism, like in multiunit Yankee auctions at Ubid.com, and if there is a going-going-gone

[6]Notable exceptions to this approach are Engelbrecht-Wiggans (1987) under the independent private-values model and Harstad (1990) under the common-values model.

period, it may be better to bid once early and again at a later time. From the bidders' perspective, an early bid gets a foot in the auction door. It is also likely to provide an exogenous signal about the level of competition. Both Ubid and eBay promote early bidding behavior.

We are aware of only two other studies that have attempted to model the bidders' arrival process into online auctions. Vakrat and Seidmann (2000) empirically found that the minimum initial bid, which is positively correlated with TOE, is negatively correlated with the number of bidders. They also found that the overall arrival process, collectively represented by the time of entry and the time of exit, influences whether an increased dispersion in bidders' valuations leads to an increase or decrease in an auction's price. In the context of group-buying (a different dynamic pricing electronic market than considered here), Kauffman and Wang (2001) found that the number of existing orders has a significant positive effect on new orders placed during each three-hour period. This result indicates the presence of a positive participation externality.

Time of Exit (TOX)

To couple the auction's endogenous entry process with its final price formation process, we also need to look at bidders' time of exit (their last bid). We hope to conduct a multi-attribute classification. TOX, when combined with TOE, lets us examine interaction effects among several dimensions of bidding strategies. In some implementations of the Yankee mechanism, a bidder's time priority is established by her first bid; thus, there is an incentive to bid early. Yet in related single-item eBay auctions, many experienced bidders do not enter until the last minute to avoid early price wars and signaling (Roth and Ockenfels 2002). This prevalent behavior in eBay has been termed *sniping*. Given the relative ease of connecting to an auction Website (as opposed to traveling to an auction house), the two conflicting incentives could be easily resolved by adopting the following strategy: place one early bid to establish time priority, and then snipe during the auction's closing stages to compete at the margin. Hence, rather than observing just one dimension (namely, the time of entry), we include the time of exit in the analysis to identify more-complex and more-interesting bidding patterns. Note that bidders using both TOE and TOX in their bidding strategy will place multiple bids in an auction, which leads us to the next variable of interest.

Number of Bids (NOB)

NOB refers to the frequency with which a bidder updates her bids and so reflects her level of involvement in an auction. It is also a proxy for the value of bidders' time. It is intuitive to assume that bidders with higher bidding cost will bid less frequently than those with lower bidding costs. Consider three different users: first, an extremely busy but sophisticated user who is adept at obtaining exogenous pricing information (say, using price-comparison agents such as mysimon.com) for products; second, a naïve bidder who does not fully understand strategic behavior and has very little time to monitor an auction; and third, a gamer who simply enjoys the competition of outbidding fellow bidders. The single common factor that distinguishes these three bidders is the total number of bids (NOB) they make in the progressive Yankee auction.

Internet auctions typically take longer than their face-to-face counterparts and hence present a significantly different bidding-cost structure. In addition to the fixed cost of the Internet connection fee, a monitoring and bidding cost exists. The latter includes the opportunity cost of dialing up to the Internet, locating the auctioned item, filling out the bidding form, and confirming the bid, as well as the overall opportunity cost of foregoing alternative solutions like using a posted price (Easley and Tenorio 2002). These costs can be significantly higher than the corresponding bidding costs in traditional counterparts such as an English auction at an auction-house. High bidding costs can deter a bidder from conducting the successive bidding (also known as *ratchet bidding* or *pedestrian bidding*) that is common in traditional auctions. On the other hand, auction sites like eBay and Ubid make bidding agents available to help reduce this cost. These agents typically behave in a pedestrian manner, bidding the minimum required bid at any given time. It is not clear whether this strategy dominates from the perspective of winning an auction and/or maximizing surplus.

Herschlag and Zwick (2000) describe a type of bidder addicted to online auctions. Again, this phenomenon underscores the importance of recognizing different bidder behaviors. If these addicts constituted the majority of bidders, a sealed-bid auction would be less popular than auctions offering both posted price and auction mechanisms.

If an auctioneer's objective is to attract Web traffic, which may be the case if large numbers of bidders are addicts, then higher levels of NOB would give tertiary benefits from prolonged exposure to the Website. On the other hand, if the auctioneer is trying to get bidders to reveal their maximum willingness to pay early on, as in the case of eBay, then high levels of NOB could be a design concern. High levels of NOB correspond to a pedestrian bidding strategy or to the use of automated bidding agents programmed to behave in a pedestrian fashion.

Time of entry (TOE), time of exit (TOX), and number of bids (NOB) must be considered jointly. They meet the criteria of being *observable, theoretically relevant, and manipulable* by mechanism-design changes.

Classification Methodology

Automated Agent-Based Data Collection

We programmed an automated agent to capture information directly from auction Websites. The HTML documents containing a particular auction's product description, minimum required bid, lot size, and current high bidders were captured every five minutes. The raw HTML data was then piped into a Visual Basic parsing module that condenses the entire information for an auction (including all of the submitted bids) into a single spreadsheet. Excel was initially used to identify the levels of our three variables. We were careful to screen out auctions in which (1) sampling loss occurred (due to occasional server breakdowns) or (2) insufficient interest existed in the auction (some auctions did not attract any bidders). Data collection lasted over two non-consecutive six-month periods in 1999 and 2000. There was a year's gap between the end of the first data collection and the start of the second. Because one of our objectives is to look for any longitudinal shifts in aggregate strategic behavior, the gap in the data-collection periods ensures the discontinuity required to count experience and exposure as a factor.

There are 4,580 distinct bidders in our dataset. One consequence of the online environment is that, after the one-time registration cost, there is next to no cost for visiting an auction site and placing a ridiculously low bid. Such frivolous bidding could potentially introduce bias in data analysis. Therefore, we defined a bidder as frivolous if his final bid was less than 80 percent of the value of the marginal bid. After performing a series of data cleaning and transformation exercises, we obtained 9,025 unique bidding data points from 3,121 valid bidders participating in 229 auctions. All of the auctions sold computer hardware or consumer electronics. We stored this information in a normalized Access Database to facilitate querying.

Data Analysis of K*-Means Clustering*

We used an efficient *K*-means clustering approach to evaluate heterogeneity in bidding behavior. A key factor in choosing this method was its proficiency in handling large datasets like ours. Our bidder data point is a vector of three variables: NOB, TOE, and TOX. If heterogeneity exists along these three dimensions, we expect the data vectors to form several clusters in the three-dimensional space. Well-formed clusters are characterized by small intra-cluster distance and large inter-cluster distance.

The algorithm partitions N data points into K disjoint subsets s_j, each containing n_j data points, to minimize the sum-of-squares:

$$J = \sum_{j=1}^{k} \sum_{n \in S_j} \left| x_n - u_j \right|^2 \qquad (1)$$

x_n is a vector representing the n^{th} data point and u_j is the centroid, the center of mass, of the data points in s_j. The algorithm consists of a re-estimation procedure that initially assigns the data points to the K sets at random. The centroid is then computed for each set. These two steps are alternated until no further change occurs in the assignment of the data points. Because the K-means algorithm starts with a specification of K number of clusters, it converges to local optima. A potential limitation of this approach is the *a priori* specification of the number of clusters, K. In our context, we do not know in advance how many different bidding behaviors exist. To address this problem, we developed a method of obtaining an efficient clustering similar to Ray and Turi's (1999) method. This procedure iteratively tries out different values of K and selects the one with the highest dissimilarity ratio. The dissimilarity ratio measures the dispersion of the different clusters.

To illustrate the method, first consider the average distance of each point to its local cluster center: *intra-cluster distance*. Clustering with the smallest intra-cluster distance is usually preferable. Because intra-cluster distance is relative to the number of clusters, a large number of clusters generate a small intra-cluster distance. However, generating too many clusters can be avoided by simultaneously considering *intercluster distance*. Intercluster distance is represented by the minimum distance among the different clusters. The larger this amount, the more dispersed the clusters are. Dissimilarity ratios are calculated by dividing intercluster distance by intra-cluster distance. The most-valuable clustering has the largest dissimilarity ratio.

Table 1 shows the dissimilarity ratios for the data from 1999 and 2000. The ratio initially increases and then decreases as K increases, with the largest dissimilarity in both cases occurring for K = 5. Therefore, the analysis identifies five distinct classes of bidders in each year.

ANOVA is typically used with K-means clustering to test the null hypothesis that no significant differences exist among the cluster centers.[7] The results in Tables 2 and 3 show that the null hypothesis is rejected for both years.

Bidder Strategy Analysis

This section discusses the strategic implications of different bidder behaviors as represented by the five clusters in each year.

1999 Bidder Classes

Table 4 contains the classification results for the 1999 data. The values present descriptive statistics of the data in each cluster.

We name each class of bidders based on the unique characteristics conveyed by the corresponding parameter values. The first cluster is *early evaluator*. These bidders place just one bid during the early stages of the auction, possibly reflecting their maximum willingness to pay. A *middle evaluator* differs only in that their one maximum bid is submitted in the middle of the auction. This could reflect either their arrival process or the fact that they may simply observe the auction's initial progress and base their bids on the actions of other bidders. Both strategies show that bidders think they can assess the true

[7]While there is no consensus on what constitutes an appropriate test for "goodness" of clustering, the rejection of the null hypothesis of ANOVA, the descriptive statistics for different clusters, and the ability to meaningfully interpret different clusters are considered primary ways of identifying a good clustering.

Table 1. *K* = 5 Has Highest Dissimilarity Ratio for Both Years

	K	3	4	5	6	7	8	9	10
Dissimilarity Ratio	***1999***	0.305	0.509	**0.514**	0.509	0.456	0.414	0.404	0.397
	2000	0.308	0.308	**0.430**	0.423	0.346	0.338	0.332	0.331

Table 2. 1999 Cluster Result ANOVA

Variable	**Mean Square Cluster**	**Mean Square Error**	**F**	**Significance**
Number of Bids	108.940	.312	348.823	.000
Time of First Bid	1377.022	1.300	1059.564	.000
Time of Last Bid	857.199	.935	916.585	.000

Table 3. 2000 Cluster Result ANOVA

Variable	**Mean Square Cluster**	**Mean Square Error**	**F**	**Significance**
Number of Bids	1057.672	1.191	888.139	.000
Time of First Bid	1304.543	2.106	619.569	.000
Time of Last Bid	1343.145	1.779	755.195	.000

market value of items being auctioned and try to bid that amount early to win. If their hypotheses were correct, we would expect them to pay less than other winners. On the other hand, they may run the risk of bidding more than required to win. Evaluators minimize the time cost of monitoring auctions. Although they may pay more than other winners, they gain a risk-aversion premium by minimizing the chance of being priced out of an auction.

The *opportunists* in the third column are late bidders. While related to snipers in single unit eBay auctions (Roth and Ockenfels 2002), opportunists differ from snipers because of the existence of a going-going-gone period in Yankee auctions. In addition, because of the larger strategic space in multiunit auctions (in the form of multiple potential winning slots), the notion of *last-minute bidding* (Roth and Ockenfels 2002) needs to be extended to our notion of *late bidding*.

The fourth column in the 1999 data corresponds to what we call the *sip-and-dippers* class of bidders. These bidders usually place two bids. They bid once early in the auction, clearly to establish their time priority[8] and perhaps to assess the competition. They subsequently revise their bids only toward the end of the auction. These bidders are behaving strategically. They incur little time cost, but they enter the auction early to hold a time priority. Note that such behavior is practical only in an online environment.

[8]Ubid clearly indicates the time of a bidder's first bid as well as the time of the latest bid.

Table 4. 1999 Data Cluster Centers (Time is Normalized on a 1 to 10 Scale)

		Cluster Name				
Cluster Dimensions	Descriptive Statistics	Early Evaluators	Middle Evaluators	Opportunists	Sip-and-DIpper	Participators
Number of Bids	Mean	1.11	1.20	1.7	2.12	3.86
	Standard Deviation	0.39	0.55	0.58	0.32	1.11
	Skewness	4.14	3.10	2.20	2.40	1.58
	Kurtosis	19.25	10.64	4.31	3.80	2.79
Time of First Bid	Mean	1.97	4.45	8.40	2.13	1.47
	Standard Deviation	0.99	1.33	1.09	1.50	1.08
	Skewness	–0.46	–0.45	–0.56	0.59	0.87
	Kurtosis	–1.11	0.59	0.82	–0.53	0.13
Time of Last Bid	Mean	2.09	4.77	8.72	8.26	8.59
	Standard Deviation	0.95	1.01	1.01	1.46	1.29
	Skewness	–0.60	0.59	–0.25	–0.98	–1.02
	Kurtosis	–0.73	–0.34	–1.22	0.67	0.81
Number of Bidders		575	524	558	283	141

The last column corresponds to *participatory* bidding (i.e., ratchet bidding or pedestrian bidding). These bidders bid throughout the auction and are characterized by early entrance and late exit. We hypothesize that they gain satisfaction from the bidding and participation process. Because participatory bidders incur a high monitoring cost and never bid more than the minimum requirement, they should extract far more surplus than the other classes. A high number of bid revisions may also capture an exogenous signal about an auction's competition level. Wilcox (2000) explained late bidding on eBay using this notion, implying that bidders revised their valuations as a result of other bids in the auction. This implies a common-value setting (such as for antiques) but fails to explain the prevalence of late bidding in other distinctly private-value settings (such as in our data set and Roth and Ockenfels's study of computers).

Even though participatory bidding behavior should yield the highest expected surplus (because of its high monitoring cost), the last row of Table 4 shows that it attracts the least number of bidders. Interestingly, on average, participators only place one more bid than sip-and-dippers. The relatively low NOB level signals that participators significantly value their time. Any technology that can reduce participators' monitoring and bidding costs is likely to make the auction process more attractive to them and will result in higher benefits for the auctioneer.

Overall, Table 4 indicates that all clusters have relatively peaked data for the number of bids.[9] Also the skewness values are similar in size and direction for clusters that may be related. For example, the mean and standard deviation for NOB are similar for early and middle evaluators. However, the mean and standard deviation for time of first and last bid are significantly different for these two clusters. Because the kurtosis values indicate relatively peaked data and the skewness is of the same order, there should be significant separation between early and middle evaluators along at least two of the three dimensions.

[9]Note that the kurtosis values reported are adjusted kurtosis values, i.e., the kurtosis for a normal distribution would be zero.

2000 Bidder Classes

Table 5 shows the classification of bidding data for 2000. The bidding behaviors are consistent with the 1999 behaviors, although subtle shifts in the bidders' strategies have occurred.

In 2000, four classes have the same bidding characteristics as those in the 1999 dataset: evaluators (early only for 2000), participators, opportunists, and sip-and-dippers. However, a new, distinct class of bidders has emerged. Bidders in this class average 15 bid revisions per auction. They also have early-entry and late-exit features. By tracking these bidders in the original bidding HTML pages, we found that they use *automatic-bidding agents* provided by the auctioneer. When using a bidding agent for Yankee auctions, a bidder specifies their maximum price. The agent automatically revises the bidder's bid if others outbid it, until the price reaches the specified maximum. This strategy is similar to participatory bidding except that its bidding costs are minimal. Presumably, bidders with high participation costs employ it.

No bidding agents existed in 1999. Also, recall that our analysis revealed that bidders disliked actively revising their bids. Thus, implementation of agent-based bidding was a good decision on the part of auctioneers. Whether this decision was due to competitive pressure (from eBay) or close attention to user behavior is unclear. Interestingly, bidders continue to distinguish themselves according to their entry, exit, and bidding costs. Indeed, the similarity between the 1999 and 2000 classes reflects remarkable stability. The only new class in 2000 (the agent class) results from a technological advance. This result indicates that our classification approach identifies an empirical regularity and that TOE, TOX, and NOB define stable microsegments of bidders.

Table 5. 2000 Data Cluster Centers (Time is Normalized on a 1 to 10 Scale)						
		Cluster Name				
Cluster Dimensions	Descriptive Statistics	Early Evaluators	Opportunists	Sip-and-Dipper	Participators	Agent Bidders
Number of Bids	Mean	1.24	1.40	2.45	5.99	15.56
	Standard Deviation	0.51	0.81	0.82	1.72	6.12
	Skewness	2.10	2.48	1.33	0.82	1.70
	Kurtosis	3.54	6.92	2.13	0.22	2.63
Time of First Bid	Mean	1.99	7.55	1.22	1.93	1.50
	Standard Deviation	1.49	1.55	1.10	1.85	1.57
	Skewness	0.63	0.14	1.15	0.79	1.16
	Kurtosis	–0.79	–1.22	0.77	–0.77	0.80
Time of Last Bid	Mean	2.53	8.08	8.02	7.53	7.81
	Standard Deviation	1.88	1.56	1.41	2.41	2.19
	Skewness	1.06	–0.28	–0.16	–0.85	–0.82
	Kurtosis	1.32	–1.30	–1.06	–0.37	–0.69
Number of Bidder		409	362	101	127	41

Middle-evaluators—bidders who enter at the middle of an auction—are absent from the 2000 dataset. The descriptive statistics for the early evaluators are quite similar in 1999 and 2000, leading us to believe that clustering has not simply aggregated the early and middle evaluators. We believe that two factors underlie the disappearance of middle evaluators:

(1) Bidders learned the importance of bidding early to get time priority. Thus, they started bidding early to increase their chances of winning with a single bid. This outcome is evident in the top-left cell of Table 6, where middle evaluators have a significantly higher winning percentage than early evaluators. Note that time priority is more important for evaluators and sip-and-dippers because they make relatively fewer bids.

(2) Bidders have improved at estimating their bid at an early stage of an auction. (As we show in the next section, middle evaluators seem to bid higher—perhaps influenced by higher minimum bid requirements later in the auction—than early evaluators.)

Outcome Analysis of Winning Percentage

We first determined whether the strategies differ in the winning percentage they yield to their adopters. To do so, we tested the following hypothesis using single-factor ANOVA with five levels representing the different types of bidders.

> ***H1:*** *All bidding classes have similar likelihoods of winning, as reflected in the proportion of winners versus losers.*

Tables 6 and 7 display the summary results from the ANOVA test for the two years. The significant F-values indicate that we can reject the null hypothesis of equality of mean winning percentage among the different bidder classes for both years.

Subsequently, to compare the bidding strategies with each other, we performed pairwise hypothesis tests on the differences between winning proportions. To deal with the α-inflation problem associated with pairwise comparisons, we used the Bonferroni adjustment to keep the experiment-wide error rate to a level equal to 0.05. This adjustment requires that the acceptable α-level be divided by the number of comparisons we intend to make—in our case 10. Thus, we consider a test statistic to be significant if the associated p-value is less than 0.005.

Tables 8 and 9 summarize the results of hypothesis tests for 1999 and 2000 respectively. Positive amounts imply that the row class has higher average winner proportions than the column class; lower amounts imply lower proportions. Test statistics marked with an asterisk indicate that they are significant at the Bonferroni-adjusted overall α-level of 0.05.

The average winning percentage indicates what fraction of a certain bidding strategy resulted in a win. Opportunists and sip-and-dippers have significantly higher winning proportions than participators, evaluators, and agent bidders. This result reflects that opportunists and sip-and-dippers are generally more eager to win. It will be interesting to see, therefore, whether they are willing to pay a higher price in an auction. Evaluators, participators, and agent bidders tend to be more cautious. For instance, agent bidders and most participators bid only a minimum required increment each time. Evaluators estimate a value for the product, submit a bid that reflects their valuation, and do not update their bid. Agent bidders use the bidding agent to facilitate automatic bidding until it reaches their predetermined highest bid. The strategies adopted by these bidders are less focused on winning than those of late bidders and more focused on staying within a budget. They are geared toward maximizing surplus.

Table 6. ANOVA—Winning Proportions (1999 Data)

Source of Variation	SS	df	MS	F	P-value	F criteria
Between Groups	49.066	4	12.266	63.465	1.12E–50	2.376
Within Groups	401.246	2076	0.193			
Total	450.311	2080				

Table 7. ANOVA—Winning Proportions (2000 Data)

Source of Variation	SS	df	MS	F	P-value	F criteria
Between Groups	17.814	4	4.454	19.469	1.76E–15	2.380
Within Groups	245.448	1073	0.229			
Total	263.262	1077				

Table 8. Pairwise Comparison: Difference of Winning Proportions (1999 Data, 2,081 Bidders)

	Cluster Name			
t value (Average Winning %)	Early Evaluators (15%)	Middle Evaluators	Opportunisits	Sip-and-Dippers
Middle Evaluators (22%)	3.13*			
Opportunists (51%)	14.00*	10.50*		
Sip-and-Dippers (48%)	10.37*	7.85*	–0.48	
Participators (24%)	2.31	0.42	–6.70*	–5.58*

Table 9. Pairwise Comparison: Difference of Winning Proportions (2000 Data, 1,040 Bidders)

	Cluster Name			
t value (Average Winning %)	Early Evaluators (15%)	Opportunists	Sip-and-Dippers	Participators
Opportunists (70%)	5.21*			
Sip-and-Dippers (74%)	4.75*	1.19		
Participators (41%)	–2.27	–5.99*	–5.75*	
Agent Bidders (27%)	–3.93*	–6.67*	–6.61*	–2.02

Outcome Analysis of Surplus

Before calculating a bidder's relative surplus, the bias that arises from the absolute dollar value of the auction must be eliminated. To do so, we calculate the normalized loss of surplus as

$$\text{Normalized loss of surplus} = \frac{\text{Winning price} - \text{Marginal price}}{\text{Marginal price}}$$

where the *marginal price* is the lowest winning price. We are interested in determining how the various strategies compare in creating surplus. Yankee auctions implement discriminatory pricing mechanisms. Therefore, each winner pays his own bidding price. Any amount paid above the marginal price is the "money on the table."

The analysis is similar to the analysis of winning percentage. We use ANOVA to test the overall equality of means. If ANOVA suggests significant differences in the mean loss of surplus, we conduct pairwise tests to compare the bidder classes with each other. Our initial hypothesis is

> ***H2****: All bidding classes have the same level of normalized loss of surplus.*

Tables 10 and 11 present the summary results from a single-factor ANOVA for the years 1999 and 2000. As before, the single factor has five levels representing the different types of bidders.

In 1999, we are unable to reject the null hypothesis of equality of mean normalized loss of surplus among the different bidder classes. Thus, we do not pursue any further pairwise comparisons. In 2000, however, a significant difference in the mean normalized loss of surplus exists among the five bidder classes.

It is interesting to relate this phenomenon to two other distinguishing features of the year 2000 bidder classes. Recall, the middle evaluators disappeared in 2000. Also, note from Tables 8 and 9 that the overall winning percentages for 2000 are higher than those for 1999. Together, these phenomena suggest that greater separation exists among the strategies in 2000. We believe these results reflect that bidders better execute their chosen strategies in 2000.

To compare the 2000 bidder classes with each other, we conducted Bonferroni-adjusted pairwise testing. A test statistic is significant if the associated p-value is less than 0.005. These are marked with an asterisk in Table 12. Because the measurement is on the loss of surplus, note that a positive (negative) statistic means the row class has higher (lower) average normalized loss of surplus than the column class.

The results indicate that the agent bidders are best at maximizing surplus. Next best are participators, followed by opportunists, sip-and-dippers, and evaluators. On average, early evaluators have the largest losses of surplus and highest standard deviation among all classes.

A key element in determining the effectiveness of the evaluator strategy is a bid's proximity to the marginal price. Informed bidders bid early and close to the marginal price to help maximize their surplus. A significant proportion of early evaluators, however, bid high early and leave significant money on the table. Participators are cautious and avoid bidding higher than necessary. Like early evaluators, agent bidders preset a highest bid. The automatic-bidding agent will always bid a minimum required amount, however, rather than leave money on the table. Because of their late bidding, opportunists and sip-and-dippers increase their likelihood of winning but leave money on the table.

Another research objective we had was to determine whether users' bidding strategies evolved over time. We study this question by comparing the proportions of winners in each class in 1999 and 2000 (Figure 2).

From 1999 to 2000, a higher percentage of bidders adopted the opportunistic strategy, while fewer adopted the early-evaluator strategy. Because evaluators leave the most money on the table, it is not surprising that bidders learn through experience to avoid this strategy. Once the novelty of online auctions wears off, bidders become more serious and adopt superior strategies.

Table 10. ANOVA—Normalized Loss of Surplus (1999 Data)

Source of Variation	SS	df	MS	F	P-value	F criteria
Between Groups	0.025	4	0.006	1.261	0.284	2.385
Within Groups	3.428	698	0.005			
Total	3.563	702				

Table 11. ANOVA—Normalized Loss of Surplus (2000 Data)

Source of Variation	SS	df	MS	F	P-value	F criteria
Between Groups	0.222	4	0.056	4.016	0.003	2.385512
Within Groups	9.076	656	0.014			
Total	9.298	660				

Table 12. Pairwise Comparison: Loss of Surplus (2000 Data)

	Cluster Name			
t value (Average Winning %)	Early Evaluators (7%)	Opportunists	Sip-and-Dippers	Participators
Opportunists (5%)	–1.86			
Sip-and-Dippers (6%)	–0.62	1.07		
Participators (2%)	–3.3*	–2.6*	–2.57*	
Agent Bidders (0%)	–5.7*	–8.79*	–4.94*	–3.75*

Another trend in 2000 is the small proportion of bidders starting to make use of the bidding agent provided by the auctioneer. The auctioneer facilitates the agents for several reasons. First, bidding agents help reduce the pressure of late bidding by allowing the bidders to set their high bid early. Second, it assumes some of the user's bidding costs in the hope that more bidders will participate. Third, if all bidders place high bids through agents, the auction is transformed into a sealed-bid auction where the highest bidder wins. In 2000, the small number of bidders who used agents realized the largest surplus. Recall from the discussion following Table 7, however, that agent bidders have a lower winning likelihood than opportunists and sip-and-dippers.

Figure 2 shows that most bidders are either opportunists or early evaluators who bid infrequently. Thus, many bidders place a high value on their time, which should motivate auction designers to reduce the bidding cost.

User Learning Effects

We also wanted to isolate repeat bidders to see whether they learned from experience. Unfortunately, we obtained insufficient data on bidders who bid in multiple auctions. Thus, our findings here are tentative.

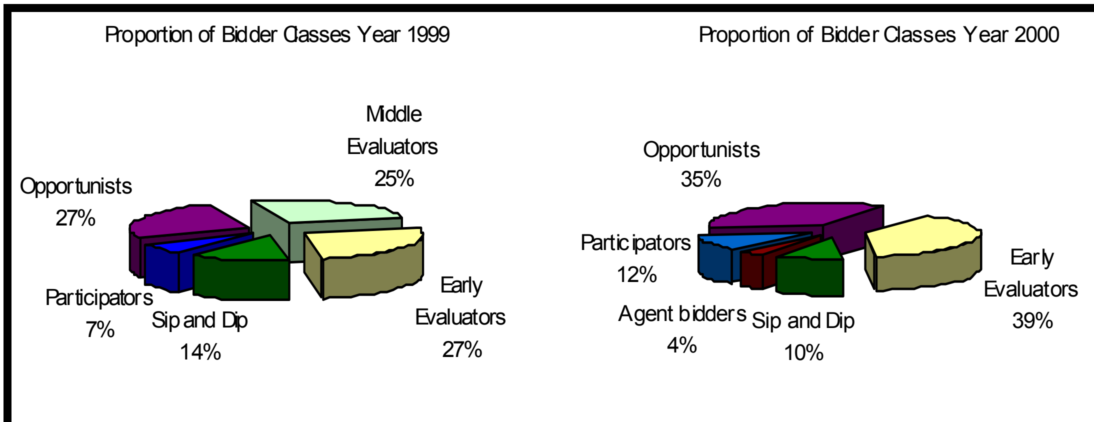

Figure 2. Change in Bidder Classes (1999 to 2000)

We observed 92 repeat bidders. Among the repeat bidders who won at least once, 70 percent improved performance, 15 percent had no change, and 15 percent dropped in performance. In addition, we observed that 57 percent of the repeat bidders switched from one strategy to another. Bidders' strategies frequently switch between early evaluators and opportunists and among sip-and-dippers, participators, and agent bidders. However, no bidder switches *between* participator and opportunist, and no bidder switches *from* a participator *to* evaluator. One bidder switched from opportunist to participator, and another switched from evaluator to participator. These results indicate that bidders exhibit a bidding pattern within a range of risk preferences and bidding costs.

Bidders who improved avoided being evaluators, bid less aggressively (using only the minimum bid increment), delayed bidding (to observe signals from other bidders), and sometimes bid more frequently at the end. We also found some evidence of bidders taking advantage of time precedence by bidding early.

Because we have identified five bidding strategies and not all repeat bidders won, we had insufficient data to perform rigorous statistical tests. Our taxonomy provides a framework for future researchers using larger data sets to further explore learning effects.

Application of the Bidder Taxonomy

Our approach to examining bidder behavior in online auctions reveals significant empirical regularities, which lead to our taxonomy of bidding behavior. The taxonomy identifies five distinct bidding strategies in Yankee auctions. This result can be viewed as a micro-segmentation of the user base of online auctions, and it has interesting practical applications in improving the design of such auctions. In addition, knowledge of any domain-specific strategy dominance can be embedded within "smarter" bidding agents.

Designing Smarter Bidding Agents

Bidding has a high participation cost for many bidders. *Automated agents* reduce bidding costs. However, the motivations of those who provide these agents need to be considered. Ubid's "Bid

Butler" and eBay's proxy bidding agent are examples of agents that have incentives aligned with sellers. Often, the auctioneer is the seller (e.g., Ubid), or the auctioneer's revenue is directly proportional to the selling price of items (e.g., eBay).

Our bidder behavior taxonomy can help with the design of third-party bidding agents that are aligned explicitly with the buyer. Smart bidding agents are currently in their infancy. Bapna (2003) contrasts the architecture of two third-party bidding agents in the case of the strategically simple, single-item auctions on eBay. Both agents employ sniping behavior, which is considered optimal in auctions (like eBay) with a hard closing time. If such agents were created for more-general, more-complex multiunit auctions, it would be a clear sign of a maturing market. Ubid's Bid Butler follows a simplistic participatory strategy. Our empirical findings show that it does not maximize the expected surplus of its users because it does not recognize the combinational aspects of multiunit auction bidding. A numerical example shows that the same initial valuation endowment yields different surpluses when users bid at different times (Bapna et al. 2003a). This example assumes that all participants want to adopt a participatory bidding strategy, which is consistent with the strategy adopted by current bidding agents provided by Ubid and Onsale.

Example 1 — Consider the following hypothetical scenario: Let there be three items for sale, let the bid increment be \$5, and let the opening bid be \$9. Let there be four individually rational bidders, all adopting the participatory strategy. Let them be A, B, C, and D with true valuations of \$100, \$105, \$106, and \$107 respectively. Let A be the marginal consumer.

- Consider (after a certain time the auction has been running) the case if we observe the following sequence of progressive bids: D(89)—C(89)—B(89)—A(94)—B(94)—C(94)—D(99)—C(99)—B(99)—STOP. At this stage, A, the marginal consumer, will have to bid \$104 to get in. He will not because his valuation is \$100. Thus, the total revenue equals \$297, and B, C, and D win at \$99 each.
- Next, consider the following sequence of progressive bids: B(94)—C(94)—D(94)—A(99)—D(99)—C(99)—B(104)—C(104)—D(104)—STOP. Observe that A, the marginal consumer, is the first to get into the winners list and hence the last to get out at that level. At the terminal stage, A would have to bid \$104 to get in. He will not because his valuation is \$100. Thus, the total revenue equals \$312, and B, C, and D win the same auction at \$104 each.

Clearly, if we were B, C, or D, we would prefer to maximize our chances of winning at \$99 rather than at \$104. Bidding the marginal price is achieved by coding a smart agent to "jump-bid," ensuring that it was the first to bid in the third-to-last round, and hence the last to get outbid at that level. This necessitates ensuring that the agent is not the first to get into the winners list at the penultimate level. ■

The above example illustrates a case in which bidders are likely worse off by adopting the available pedestrian bidding agents. It shows how an understanding of the bidder taxonomy facilitates the creation of a jump-bidding agent. Such agents can maximize a bidder's expected surplus if programmed to make more than the minimum bid. Recall from Table 7 that opportunists and sip-and-dippers outperform current implementations of the bidding agents with respect to winning likelihood. These two bidder types are likely to dislike the current Bid Butler because its pedestrian nature opposes their primary objective of winning. They may be bidders who have budget constraints below their valuations that limit the amount they can bid. For such bidders, surplus is not a major issue but winning likelihood is (Che and Gale 1998). With smart agents, we expect bidders will be able to specify their weights on surplus maximization and winning likelihood. To the best of our knowledge, no such smart agents exist for the multiunit auction. This is a promising application for our taxonomy of bidder behavior.

Valuation Discovery and Dynamic Mechanism Design

Another unconsidered aspect of the online auction environment is whether the technologically enhanced information gathering and processing capabilities might be used to perform real-time valuation discovery and calibration. In brief, real-time valuation discovery involves combining standard Bayesian statistical inference techniques with the bidder taxonomy to determine how much of a current bid corresponds to a bidder's true final valuation. An auctioneer could then observe each bid as it arrives and use historical valuation distribution information and bidder behavior patterns (from the taxonomy) to estimate each bidder's final willingness-to-pay. Our early experimentation shows that we can estimate a Yankee auction's final price (within 10 percent) by the 40th time percentile (Bapna et al. 2003b). This result could be useful in setting *dynamic buy-it-now* prices, which adjust themselves as the auction progresses.

The Artificial Intelligence field already employs value discovery models as components of bidding agents. For example, Parkes and Ungar (2000) use the notion of *myopic best-response* bidding strategies among agents to illustrate how proxy bidders employing this strategy can be shielded from manipulation. Myopic best-response bidders react to current information and fail to form a strategy based on an auction's complete strategic space (as would be required by traditional auction theory). Our findings and the taxonomy we have developed corroborate this notion. Participators and opportunists "myopically" maximize their surplus when they formulate their bids. In contrast, early evaluators and sip-and-dippers are more interested in maximizing their likelihood of winning. Our taxonomy can serve as the basis from which to derive valuation prediction methods for different bidding behaviors.

The dynamic calibration of auction parameters is one use of real-time valuation estimates. It has long been believed that the expert auctioneer's chant in a face-to-face auction maintains order in the auction and the movement of bids:

> $100,000, I have $100,000! $120,000! $130,000! I have $140,000 out back and $150,000! Will you give me 175? 175! 200? 200? 250? Will you give me 250? (Smith 1990, p. 9)

The expert auctioneer dynamically adjusts the bid increment, thereby maximizing the economic efficiency of the auction. A dynamic calibration mechanism for online auctions, based on the valuation prediction approach, would represent an expert system akin to the real-world auctioneer.

General Purpose, Risk-Free, Decision-Theoretic Computational Platform

The bidder behavior taxonomy can help create a test bed for exploring new possibilities in online auction design. Coupling a theoretical understanding of the revenue-generation process of online auctions (Bapna et al. 2003a) with the creation of bidding agents that replicate the bidding strategies of real-world bidders can create a simulation platform. Simulations with high inductive value should replicate the observed auction's winning bid structure statistically. Because the winning bid structure (and thus revenue) is affected by environmental parameters like bidding strategies, the winning bid structures cannot be replicated if the parameters inferred from observed auctions are not specified with appropriate granularity. If this condition is met sufficiently, the environmental parameters can then be modified to isolate and test the effects on a given auction.

In the case of Yankee auctions, the simulation platform could help investigate what impact rules of auctions like bid increment and starting bid amount have on an auctioneer's revenue. Such a tool would be cost effective and could be used *ex ante* in a dynamic marketplace, potentially avoiding many of the pitfalls that can emerge from costly entrepreneurial ventures that resemble uncontrolled field experiments.

Conclusions

We have created a taxonomy of online bidder behavior and have examined the economic impact of various bidder strategies in the context of the popular Yankee auctions. Significant heterogeneity exists in the online bidder population, a fact reflected in the five strategies we have identified. Different combinations of time of entry, time of exit, and the number of bids placed characterize these strategies. We also observed that users improve the execution of their bidding strategies over time and respond to technological advances in the market by adopting agent bidding to lower their bidding costs. Our findings indicate that agent bidders, followed by the participators, have the highest levels of surplus, while opportunists and sip-and-dippers have a higher likelihood of winning an auction. Also, the economic benefit of the agent bidder is predicated on the strategies of other bidders. In the extreme case of all bidders using the auctioneer's agent, the game is transformed into a sealed-bid auction, and bidders with the highest valuations win the items.

Our study reveals that an understanding of bidder strategies is crucial to enhancing the design of online auctions. We discuss how the taxonomy can be critical in statistically predicting bidders' valuations in real time. Finally, the taxonomy is critical to creating risk-free simulation platforms that can test the endogenous impacts of mechanism-design choices.

Several bidding strategies are currently being adopted in online markets. They all result in different economic consequences. Further research is needed to understand bidders' motivations in adopting these strategies. We expect our taxonomy of bidder behavior to provide a basis for future research.

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