Cyberspace Auctions and Pricing Issues: A Review of Empirical Findings

April 5, 2002

Abstract

This article surveys empirical findings from recent studies of Internet auctions and summarizes the theoretical insights gained from these findings. The main questions answered in this article are: What are the price formation mechanisms used in Internet auctions? What are the main causes of informational asymmetry in these online environment, and how can the extent of these asymmetries be quantified? Does observed bidder behavior conform to the theoretical predictions from game theory? How do the findings regarding bidder behavior on Internet auctions shape our theories on mechanism design?

1 Introduction

Recently, we have seen an explosion in the number and dollar volume of transactions between consumers and businesses. According to the Census Bureau of the Department of Commerce, the dollar volume of retail e-commerce in the 4th quarter of 2001 was $10 billion dollars, which has nearly doubled from $5.27 billion dollars in the 4th quarter of 1999. E-commerce accounted for 1.2 percent of retail sales in Q4 of 2001, up from 0.7 percent in 1999. Business-to-business (B2B) e-commerce, as defined by the census, was much larger. In 2000, it accounted for 94 percent of all e-commerce. The census estimates that e-commerce in 2000 accounted 18.4 percent of manufacturing shipments ($777 billion) and 7.7 percent ($29 billion) of merchant wholesale trade sales.

During the past 3 years, we have seen the entry of a number of online markets. Amazon has seen sales expand to $3.12 billion in the year 2001. The online auctioneer eBay in the year 2001 had 423 million items listed for sale in 18,000 unique categories. In addition to these high profile consumer sites, the past decade has seen a movement towards automation of securities markets and public and private procurement.

Robert Hall, in his excellent survey of electronic commerce, identifies several basic pricing mechanisms that are currently used on the net. These are posted prices, online auctions, securities exchanges and B2B procurement auctions. The simplest of these mechanisms are posted prices where the price is set in advance by the seller who markets a standardized product is marketed to a large number of customers. This pricing model includes leading retailers such as Amazon, Dell or buy.com.

In many transactions (both online and offline), posted prices may not be very effective mechanisms for pricing because buyers and sellers have private information. For buyers, their willingness to pay for an object is typically an important piece of private information that they are unwilling to reveal to a seller. Similarly, a seller's cost of acquisition for an item is frequently private information. Buyers frequently try to hide their private information. For instance, when negotiating with a seller, a savvy buyer does not start out by stating her maximum willingness to pay for the item since this information in all likelihood would raise the price the buyer would

have to pay. Similarly sellers do not wish to reveal their willingness to pay to buyers since the buyers will then have better information with which to bargain the seller down to a lower price.

Private information is an important issue in both what business models will be successful on online markets and in how buyers choose to behave. In online auctions, a large fraction (probably the majority) of items sold are unique collectibles including a diverse set of items ranging from books to coins to beanie babies. In order for the market to function well, the rules need to be designed in such a way to overcome buyers and sellers unwillingness to reveal their private information.

A striking example of how private information can play a role can be seen in the difference between a design of auctions proposed by Yahoo and the eBay auctions. At one point in time, Yahoo did not charge sellers to run auctions online. As a result, sellers listed their items with very high minimum bids and very few items actually sold. The strategy of sellers in many cases seemed to be to find the one customer, probably not very shrewd, who was willing to pay a very high price for the item, in all likelihood, much above the seller's true willingness to sell with the item. As a result, the market seemed to function rather poorly. eBay, on the other hand, charged sellers fees for listing their objects. Minimum bids were set much more reasonably and a much larger percentage of listings resulted in a sale. The point of this example is to illustrate that changes in the rules, which at first might seem inconsequential, can have profoundly different implications for how agents bid and how well the market works. It is worth noting that Yahoo has recently dropped its free listing of auctions and a much larger fraction of the auctions result in sale.

Private information is also a significant concern in B2B procurement auctions and in securities markets as well. In B2B procurement auctions, the bidders do not wish to directly reveal their cost for completing the procurement contract and the seller does not wish to directly reveal her price. A well functioning market must automate a mechanism for which the buyer and seller can come to an agreement. In securities markets, buyers and sellers may change their strategy if their identities are revealed or if information about their bids is revealed. Robert Hall notes that even in posted price markets, private information can play an important role. For

instance, Dell has been known to negotiate discounts with certain buyers (such as students and professors at Stanford University) and has them access their web site and charges customized prices. Similarly, Hall notes that the web site Grainger.com negotiates fixed discounts from the posted prices with given buyers, which are due to private bargaining (and private information!) among the buyer and seller.

In our survey, we will focus primarily on the case of online consumer auctions in order to understand the relationship between private information and the functioning of online markets. The primary reason we chose to focus on consumer sites is the availability of data. Whereas most business-to-business auction sites are accessible only to member firms, online auction sites are a great source of data for those interested in testing theories of asymmetric information and strategic behavior in markets. For example, eBay, Amazon, and Yahoo store bidding histories for all their completed auctions, and a computer program can be written to automatically download these web pages and collect data on bids and bidder/object characteristics.

2 Price Formation in Internet Auctions

There are a large number of sites that provide online auctions on the Internet. David Lucking-Reiley lists 142 different sites operating in 1998. A quick search of Yahoo reveals a far larger number of sites (in 2002) in categories ranging from horses to sporting goods to real estate and cars.

eBay is by far the most popular consumer auction site in the United States. According Nielsen/NetRatings statistics reported by AuctionWatch.com, the number of unique visitors to eBay within a given month grew from about 9 million to 12 million between November 1999 and November 2000. At Yahoo, the next most popular consumer auction site, the number of unique visitors grew from 2 million to 3 million in this time period. eBay's commissions revenue was $780 million on about $8 billion of transactions.

What is being sold on Internet auction sites for consumers? David Lucking-Reiley reports that 60% of all the sites he surveyed included auctions for collectibles. About half of the listings

on eBay can be classified as collectibles (antiques, stamps, coins, dolls and other toys, sports memorabilia). Computers, electronics, household equipment, DVD/video cassettes and music equipment comprise a quarter of the listings. Only one percent of auctions on eBay are of business related items (although some of the computer auctions can be business related).

The fact that so much of the auction volume is of collectibles and other second-hand items suggests that the emergence of online auctions has transformed the nature of second-hand goods trade between households. Before the existence of auction sites, most of this trade took place locally, with limited marketing opportunities. However, sites like eBay allow people to conduct their yard sales on a nationwide basis, instead of relying on their neighbors or local bargain hunters to clear their attics.

2.1   Auction Formats

The listings on eBay, Yahoo and Amazon, the three biggest auction sites, are organized into thousands of categories and subcategories, such as antiques, books, and consumer electronics. Within any category, buyers can sort the listings to first view the recently listed items or the auctions that will close soon. The auction site also provides a search engine that allows buyers to search listings in each category by keywords, price range, or ending time. The search engine allows users to browse completed auctions, a useful tool for buyers and sellers who wish to review recent transactions.

All of these sites employ variants of the Vickrey auction. The mechanism used on eBay is a dynamic variant of the second price sealed bid auction proposed by Vickrey, called "proxy bidding." When a bidder decides to submit a bid, she is asked by the eBay computer to enter the maximum amount she is willing to pay for the item. This is her "proxy bid." Suppose that bidder A is the first bidder to submit a proxy bid on an item with a minimum bid of $10 and a minimum bid increment of $.50. Let the amount of bidder A's proxy bid be $25. eBay automatically displays A as the highest bidder, with a bid of $10. Next, suppose that bidder B enters the auction with a proxy bid of $13. eBay still displays A has the highest bidder, but raises the high bid to $13.50. If another bidder submits a proxy bid above $25.50 ($25 plus

one bid increment), bidder A is no longer the high bidder and the eBay computer will notify bidder A of this via e-mail. If bidder A wishes, she can submit a new proxy bid. This process continues until the auction ends. The high bidder ends up paying the second highest proxy bid plus one bid increment. Once the auction has concluded, the winner is notified by e-mail. At this point, eBay's intermediary role ends and it is up to the winner of the auction to contact the seller to arrange shipment and payment details.

In Figure 1 below, we display a recent listing on eBay for six Morgan Dollars. Listings typically contain detailed descriptions and pictures of the item up for bid. The listing also provides the seller's name, the current bid for the item, the bid increment, the quantity that is being sold, and the amount of time left in the auction.

(Insert Figure with picture of information displayed to bidders)

The mechanism on Yahoo is essentially identical to the format used on eBay. Amazon uses a similar format, but, for reasons that will become clear later, chooses not to have a fixed ending time. Auctions on Amazon also close at the pre-announced ending time except in the case that more than one bid arrives during the last five minutes of the auction. With the arrival of every bid, the ending time of the auction is extended another five minutes.

2.2 Asymmetric information: Adverse selection

In many markets, particularly markets for used and possibly damaged goods, economists worry about the problem of adverse selection, that is, sellers may have hidden information about the quality of the good. George Akerlof, in a seminal paper, studied a simple model of the market for used cars. He demonstrated that if, at the time of sale, only the seller can determine the car is a "lemon", then it can be the case that there is no equilibrium where cars are sold.

Akerlof's results were quite pessimistic about the ability of markets to function when there is adverse selection. Several authors (such as Benjamin Klein and Keith Leffler) have suggested that reputation might be a mechanism that allow markets to function in the presence of adverse selection. If the seller has gained a reputation for honest and ethical behavior, such as making full disclosure of all defects in a particular product, then markets can have a positive level of

trade.

Online auction sites attempt to solve this informational problem by implementing a ratings system. For example, after each completed auction, eBay allows both the seller and the winning bidder to rate one another in terms of reliability and timeliness in payment and delivery. The rating is in the form of a positive, negative or neutral response. Next to each buyer or seller's eBay ID (which is usually a pseudonym or an e-mail address), the number of net positive responses is displayed. By clicking on the seller's eBay ID, bidders can view all of the seller's feedback, including all comments as well as statistics totaling the total number of positive, neutral and negative comments.

A number of economists have provided estimates for the value of reputation in eBay auctions. This is done by using regression to estimate how much bids increase as a function of a seller reputation. Several authors have engaged in this type of study. Three representative papers in this literature are by Daniel Houser and John Wooders, Mikhail Melnik and James Alm, and Doug Bryan, David Lucking-Reiley, Naghi Prasad, and Daniel Reeves. All authors find that the amount of negative feedback reputation negatively correlated with the sale price and that the amount of positive feedback is positively correlated with the sale price.

A rather surprising finding of these papers is that prices are not very responsive to observed feedback ratings. For instance, Melnik and Alm estimate that a seller who doubles her rating from 452 to 904 will only increase the sale price of the objects in their sample by $.18 (an average object in their sample sells for $32.00). They estimate similarly that the impact of negative ratings seem to be rather small. Houser and Wooders estimate that a ten percent increase in positive feedback points will increase the winning bid by only 0.17%. A ten percent increase in negative comments reduces the sale price by 0.24%. Lucking-Reiley, Bryan, Prasad, and Reeves find that a 1 percent increase in the seller's positive feedback raises prices by 0.03% and a 1 percent increase in negative feedback decreases prices by .11%.

We believe that these results are likely to significantly understate the returns from having a good reputation. In Houser and Wooders, no seller has more than 12 negative feedback reports, in Melnick and Alm, the maximum is 13. Lucking-Reiley, Bryan, Prasad, and Reeves

do not report this figure.

In Bajari and Hortacsu, only the sellers with thousands of sales had more than 10 negative feedback points. For sellers with more than 100 sales, we saw no seller with more than 1 percent of its feedback as negative. If a similar pattern holds in these studies, then there are very few if any sellers who are both large and have a habit of getting a significant fraction of negative feedback. Since getting positive feedback requires effort on the part of sellers, it appears that sellers are making efforts to avoid negative feedback, such as making sure that their shipment are on time and their descriptions of the items for sale are accurate.

From a buyer's viewpoint, what he should care about is the probability of a bad transaction. If we take the number of negative or neutral feedbacks divided by the total amount of feedback as the beset estimate a bidder could make of the probability of having a bad transaction, then in the data, there simply aren't any firms to trade with (with more than 100 transactions) with whom the probability of a bad transaction is high. From a buyers viewpoint, almost all of the sellers in the market either have a good track record for satisfying customers (or at least satisfying them enough not to get bad feedback) or are newcomers without a good or a bad track record. eBay reports that only a handful of transactions out of every million result in a complaint to their Safe Harbor.

As a result, the regression results presented by the authors mentioned above can only tell us about the value of a reputation for the firms observed in the sample, all of which seem to be well behaved! We believe that the lack of negative feedback as a percentage of total feedback is a measure of the worth of having a good reputation. Also, the number of markets (Yahoo, Amazon, anyone else!) that have copied eBay's reputation system is an indication of the benefits to tracking the reputation of buyers and sellers. Since it is costly for these measures to be implemented in the market, presumably there must be benefits (real or perceived) to having this system for the buyers, sellers or market makers (or possibly all three!).

2.3 Asymmetric Information: The Winner's Curse

One thing that economists always worry about in auction markets is the winner's curse. The winner's curse was first discussed by three Atlantic Richfield engineers Capen, Clapp and Campbell who considered the problem of bidding by firms for leases to drill offshore oil. The idea is fairly simple and can be illustrated by the following experiment that is often conducted in undergraduate economics courses or in MBA courses. The professor comes into class and announces that he is going to auction off a large jar of pennies. The students are allowed to visually inspect the jar without opening the jar. Before bidding, it is likely that all students make an estimate of the dollar value of pennies contained in the jar. Invariably, the student who wins the auction loses money because the winner has an overly optimistic estimate of the number of pennies in the jar. This is referred to as the winner's curse.

In game theoretic models of auctions developed by economists, all bidders are rational, that is, they maximize their (expected) utility given their (correct) beliefs about the probability distribution of bids that will be submitted in the auction. Economists focus mainly on two different types of informational environments: one in which bidders have "private" valuations for the goods , and one in which the object has a common value to all bidders.

In a private value auction, each bidder values the object differently (ignoring any ties), and knows this valuation before placing a bid. In particular, a bidder's ex-post utility from winning the object is not affected by her knowledge of other bidders' valuations (although this knowledge might let her change her bid). Therefore, the winner in a private value auction does not suffer from a winner's curse.

In contrast, in a common value auction, winning the object gives all bidders the common return of v dollars (this is analogous to the true number of pennies in the jar). However, the bidders do not observe v, instead each bidder i receives a noisy signal x_i of the object's "true" worth v. Rational bidders should forecast that they will only win the auction when they have the highest signal x_i of v.

If there are a large number of bidders, then it is very likely that, conditional on winning, a bidder's signal will be significantly more than v. Therefore, if bidders rationally anticipate

the winner's curse, they should bid more conservatively as the number of bidders increases, all else held constant. Bajari and Hortacsu attempt to "test" for the winner's curse, using a methodology first suggested by Harry Paarsch by attempting to estimate the effect of increasing the number of bidders in the auction for a set of coin auctions held on eBay in 1998. If the winner's curse is present, then the winning bids might decrease as the number of bidders increase. They find that this holds in a variety of econometric specifications.

However, in order for the above regressions to provide acceptable tests of the winner's curse, Bajari and Hortacsu must account for the participation decisions of the bidders. Unfortunately, a natural instrumental variable strategy leading to exogenous variation in the number of bidders across auctions is difficult to conjure in this case. One possibility is to utilize technical problems experienced with the web site, which might cause some bidders not to be able to participate in the auctions. However, we have not been able to locate data from outage periods of the major auction sites. Another possibility is to use auctions' ending dates/times as a variable correlated with entry. Unfortunately, this variable is not exogenous in the sense that sellers strategically choose when to list their auctions.

In order to control for the selection bias introduced into the above regression to assess the importance of the winner's curse, Bajari and Hortacsu estimate a structural model of bidding in eBay auctions. A structural model is a fully specified description of all of the economic primitives, such as the payoffs for the agents, the information available to the agents and so forth. While estimating a structural model commits the econometrician to a fairly specific description of bidder behavior, an advantage of this approach is that it allows the econometrician to make certain inferences that would not be possible only through the use of regression analysis.

In the structural model estimated by Bajari and Hortacsu, the entry decisions of the bidders are modelled in the following manner: a pool of potential bidders arrive at the auction site. These potential bidders are ex-ante identical. However, by incurring a cost, the potential bidder can form an estimate of the value of the object, and if this estimate is high enough (at least higher than the minimum price charged by the seller), she places a bid. Conditional on the decision to participate, the profit-maximizing bidding strategy takes into account the "winner's

curse." However, since the bidder does not know exactly how many competitors she is going to face, her bid depends on the distribution of the bidders she expects to participate in the auction. For this expectation to be rational, however, the entry decisions of the bidders needs to be subject to a zero-profit condition. Since bidders are ex-ante identical, they all choose to enter the auction with probability p, where p is determined by the zero-profit condition, which, in turn, depends on the expected profits of the bidders in the auction. That is, entry decisions of the bidders are the result of a "mixed strategy" equilibrium of the participation game. Bajari and Hortacsu argue that, given this mixed strategy equilibrium, the equilibrium distribution of bidders participating in a given auction will be approximated well by a Poisson distribution, if a the number of potential bidders eyeing each auction is large. Since this assumption seems to be confirmed in their data, in their structural model, Bajari and Hortacsu let the expectation of each bidder regarding distribution of the number of bidders in the auction to be a Poisson random variable, whose mean depends explicitly on auction characteristics such as the book value of the object, the presence of a blemish, and the minimum bid/reserve price policy of the seller (all of these variables enter into the expected profit calculation made by the bidders).

Bajari and Hortacsu find that for a "typical" auction in their data set (that is, when all variables, such as book value, the presence of a blemish and so forth) are set to their sample means, A bidder with an estimate equal to the average book value of a coin in their data set of \$47.00 should only bid \$41.50. That is, bidders, due to the winner's curse will shade their bid to twelve percent under their estimate. Bajari and Hortaçsu also estimate the effect of adding an additional bidder to a "typical" auction. They find that bids fall about 3.2%. Their regression analysis provides a similar estimate (make sure this is right!).

In summary, Bajari and Hortaçsu find that the winner's curse does seem to be present in the markets, but that sellers seem to be doing a fairly good job of providing accurate information about the objects for sale so that customers only shave their bids by 12 percent due to their uncertainty about the object's worth.

2.4 Late Bidding

A salient fact that a number of researchers have noted about bidding on online auctions is that bids frequently arrive very late in the auction. For instance, Bajari and Hortacsu in their survey of eBay coin auctions report that the median winning bid is submitted after 98.3% of the total auction has elapsed (the last 73 minutes of a 3 day auction) and 25% of the winning bids arrive after 98% of the auction time has elapsed (the last 8 minutes of a 3 day auction). Roth and Ockenfels (2001) report similar figures for computer and antiques sold on eBay. Both researchers find a significant fraction of bids that have been carefully timed to arrive at the very last second. This practice is referred to as "sniping".

The last-minute bidding phenomenon has attracted a good deal of attention among academic researchers. One explanation for last minute bidding is that it is due to the private information of bidders. This explanation has been advanced in Bajari and Hortacsu and in Roth and Ockenfels.

In online markets, bidders can be uncertain about the quality or true worth of the object that they are bidding for. On eBay, a large fraction of the items sold are collectibles, such as coins, antiques, and memorabilia. Purchasers of collectibles typically care about the quality of the item that they have purchased. For instance, coins have a higher value if their surface is unscratched and antiques have a higher value if they are completely undamaged. From one's computer screen, it may be difficult for a buyer to ascertain whether the object is undamaged.

Another source of uncertainty about the item is its resale value. For instance, bidders may not know how much a collectible is likely to fetch in a resale market. This is true in both online and offline markets. If the exact worth of the item to all potential buyers was public information, after all, there would be no reason to even hold an auction. Sellers could, in principal, do better by directly contacting the person who values the object the most.

Suppose that bidder A and B both has their own private estimate about the object's worth, after taking into account quality and resale. In many cases, it is natural to presume that the average of the estimates of bidder A and bidder B is a better estimate of the object's worth A's estimate alone or B's estimate alone.

Now consider bidder A's strategic choice of whether to bid early or to bid late. If A bids early, then she might possibly reveal information about her estimate to B. For instance, if A bids high early, B might infer that A values the object a lot. B might react to this by submitting an aggressive bid early. The final outcome is that by bidding high, early in the auction, A will pay more. However if A bids at the very "last second", B will not be able to infer whether A has a low bid or a high bid.

In order for this story to be true, however, it must be the case that bidders would change their own estimate of the object's worth if they knew the estimates of other bidders. A criticism of this story has been that this cannot be the only explanation of last minute bidding because last minute bidding has been observed in auctions with private values, that is, a bidder will not change her estimate of the object's worth if she knew other bidder's estimates. A good example of this might be CD auctions. If bidder A values the latest Enya CD at $12.00, knowing that bidder B values the CD at $10.00 might not change A's valuation of the CD (although it might change A's bidding strategy!). Some economists believe, anecdotally, that last minute bidding occurs in markets with private values, so there must be other incentives to bid at the last second other than a theory based on common values.

A theory developed by Roth and Ockenfels is that last minute bidding occurs because it represents a form of collusion. In their model of online auctions, there are at least two possible equilibrium. In the first equilibrium, agents bid early in the auction and in the second equilibrium, there is no early bidding and agents only bid at the last second. The advantage of the late bidding equilibrium is that it avoids a "price war" and bidders are left with higher payoffs. Roth and Ockenfels survey bidders and conclude that avoiding a price war is one reason why they bid late.

One criticism of the Roth and Ockenfels story is that their model is quite stylized and it abstracts away from entry. If bidding late leads to collusive levels of profit, then we would expect entry to occur in a market such as eBay where there are millions of potential bidders, some of which make their living scouring the market for under-priced items. If items consistently sell for less than bidder's valuations, it seems to us that this would encourage entry into the market

and this would pose problems for sustaining a collusive equilibrium.

It is our belief that there are probably a large number of possible reasons why last minute bidding could occur. At an intuitive level, we believe that one reason why last minute bidding occurs is that, if bidder A raises her bid, other bidders can only respond by either doing nothing or raising their bids in response. If there is a positive probability that A's rivals will raise their bids in response, it is optimal for A not to bid early. The reasons for raising bids in response can range from common value stories to stories of competition between bidders that early bidding generates "price wars".

Another interesting fact about late bidding derived by Roth and Ockenfels is that late bidding appears to be less prevalent on auctions held on Amazon than on auctions held on eBay. On Amazon computer auctions, 95% of the bids arrive an hour before the auction ends, whereas on eBay, we need to go to the last few minutes of the auction to get 95% of the bids. On Amazon, the ending time of the auction is extended five minutes if a new bidder arrives at the end of the auction. Thus, the auction only closes when there have been no bids for the last 5 minutes of the auction.

Roth and Ockenfels sample 480 auctions from eBay and Amazon: 120 computer auctions from eBay, 120 computer auctions from Amazon, 120 antiques auctions from eBay and 120 antiques auctions from Amazon. In this sample, they found that 89 of the 240 eBay auctions they sampled had a bid in the last minute of the auction, 29 auctions had a bid in the last ten seconds. In Amazon, however, only a single bid was submitted in the last minute! To control for the fact that Amazon auctions attract less bidders than eBay, the authors repeated this comparison using a probit regression of the occurrence of late bids on observable auction characteristics, including the number of bidders and seller reputation. Even with the added control variables, the regression results confirmed the result that there is much less last minute bidding on Amazon than on eBay.

Roth and Ockenfels argue that this is because of the hard deadline in eBay auctions. The ending time of the auction is fixed in advance on eBay auctions whereas it is not fixed in advance on Amazon auctions. They conclude that this difference in the rules is probably the

most important factor in inducing last minute bidding. After all, if the "last minute" is not fixed in advance (as it is in Amazon), sniping is by its very definition not possible.

A benefit of the going-going gone rule in online auctions is the fact that it regulates site traffic: bidders on eBay face the definite possibility that their last-minute bid might be lost in transmission. In fact, as reported by Roth and Ockenfels, there are a number of online businesses who specialize in providing "sniping software" to savvy eBay bidders: this software allows bidders to program the timing of their bids. Hence a chunk of the surplus attainable by the sellers and the bidders is extracted by such mediators.

So why does eBay not switch its mechanism to use a going-going gone rule? This might be a function of inertia, in that such a switch is sure to result in a flood of angry complaints from users who have invested into sniping software. Some sellers might also prefer to have a fixed deadline for their auctions rather than have their auction drag on due to the going-going gone feature. There are a significant number of sellers who list hundreds of auctions per day on eBay. These sellers most likely use an automated system to schedule their activities – a change in the auction rule might throw their scheduling arrangement into disarray.

An important conclusion we can take from the analysis of sniping is that bidders appear to be behaving strategically, that is, they realize that their actions are interdependent and are not taken in isolation. In the classical theory of general equilibrium, agents in the economy do not behave strategically. They simply take prices as given by the market place and choose the actions that maximize utility if they are consumer or maximize profits if they are firms. The analysis of last minute bidding suggests that participants in online auctions are savvy and spend time thinking about the consequences of alternative bidding strategies.

These empirical findings underline the subtlety of market design: even a seemingly trivial change in auction rules can cause striking changes in bidding strategies, and can cause important alterations in the revenue and informational aggregation properties of the auction mechanism. Bidders and sellers on eBay might not, a priori, be the rational agents populating game theoretic models. However, on a high volume site like eBay, it is quite likely that experimentation and/or evolutionary pressures will cause participants to learn their best-response strategies quickly, and

uncover the "strategic loopholes" of the site rules. The role of the market designer is, then, to discover and plug these loopholes.

3 Market Design Insights from Internet Auctions

A large body of work in auction theory is geared towards finding the "rules-of-the-game" that will help maximize a given welfare objective. This body of work has, until recently, been regarded as a branch of the broader literature on "mechanism design theory." However, the increasing applicability of auction theory in the design of markets like FCC spectrum auctions and deregulated electricity markets has recently given this work a more practical orientation that is tightly wedded with statistical and experimental evidence on actual behavior in these markets. As Robert Wilson, a pioneer in the use of game theory in the design of real-world markets, has put it, "market design" can now be viewed as a legitimate field of engineering, whose foundations are firmly rooted in economic theory, econometrics, and experimental economics.

Online auctions provide insights into both normative and positive aspects of market design . The normative question is "How should the market be designed and/or improved?" and the positive question is, "Given that the market is designed in a particular manner, does the behavior correspond to what the designer intended, and what causes the deviations?"

To answer these questions, a clear design objective is needed. The most "economic" design objective is to ensure the efficiency of the allocation (i.e. the person who values the object the most ends up winning it). Another popular design objective is to maximize the sellers' (or, in the procurement context, buyers') surplus. In certain settings, such as financial markets, informational efficiency of the auction mechanism is also a desirable design objective.

At first sight, the design problem of an auction theorist seems like an extremely complex task. Given any set of "rules-of-game," the theorist has to first compute the resulting strategic equilibrium of the game, and then calculate how bidders' strategies lead to different revenue or efficiency outcomes. Since the space of auction rules is quite large, finding an optimal set of rules in this manner is a very slow and arduous process – unless a concise way of parameterizing

the space of "auction rules" is devised. Fortunately, the revenue equivalence theorem of Roger Myerson does precisely that. Instead of focusing on deriving the equilibria of different auction games, the theorem relies on Myerson's "revelation principle," which focuses the problem on revenue consequences of allocation rules that are based on direct reports of bidders' valuations, rather than their bids. By imposing the restriction that the payment and allocation rules lead to truthful reports of bidders' valuations, the theorem provides a remarkably simple characterization of the revenue/efficiency frontier: in an environment where bidders have symmetric independent private values, two auction mechanisms that award the good to the bidder with the highest valuation must yield identical ex-ante expected revenues for the seller.

3.1 Why ascending auctions?

The revenue equivalence theorem provides a benchmark in which efficiency concerns make the choice of mechanism irrelevant from the perspective of revenue maximization. For example, under the assumption of symmetric independent private values, the sealed bid first-price auction yields the same expected revenue as an ascending auction or a second price auction; since all of these auction mechanisms award the good to the bidder with the highest valuation.

Given this irrelevance result, it might seem surprising that David Lucking-Reiley found that 121 of the 142 Internet auction sites he surveyed in 1998 used an ascending auction format, as opposed to a sealed-bid format (only 7 sites used a first-price sealed-bid auction and 8 used a second-price sealed bid auction).

Lucking-Reiley suggests that the use of ascending auctions makes it easier for bidders to decide which auction to participate in. On sites like eBay, in a given time there many open auctions in a given category (often of identical goods) that end at slightly different times. Bidders can choose which auction to bid on, and how much, by observing winning bids in each stage of these open auctions. In fact, a recent theoretical paper by Michael Peters and Sergei Severinov examine a setting in which there are N buyers and M sellers of an identical good, for which bidders have independent private value unit demands.They demonstrate that the following simple bidding rule constitutes a perfect Bayesian equilibrium of this game: bid

at the auction with the lowest current price and raise your bid as slow as possible, as long as it is below your valuation. When all buyers follow this trading rule, all trades will occur at a uniform price determined either by the maximum willingness to pay among the losing bidders, or the highest minimum bid set by the sellers. This is equivalent to the outcome of a "centralized uniform price auction," in which all sellers and buyers submit bids to a central market-maker, who then determines the market clearing price and, consequently, who among the bidders receives the object.

Observe that the equilibrium bidding strategy of Peters and Severinov's model requires very little sophistication from the bidders. The only information required for their decision are their own valuations, and the highest standing bids across different auctions. In particular, bidders do not have to know how many bidders are present in the auction they are bidding on. However, if the same M auctions were run as first-price sealed bid auctions, the bidding strategies of the buyers would be considerably more complicated, since the optimal bid in a first-price auction depends on how many bidders are expected to bid in the auction. Without explicit coordination among bidders, the number of bidders in a given auction is going to be a random variable from the perspective of each bidder, making her decision problem even more difficult.

Aside from this "coordination cost" advantage, ascending auctions also have distinct advantages over sealed-bid auction formats with regards to revenue extraction and informational efficiency in common value environments. A set of classic results in auction theory, this time by Paul Milgrom and Robert Weber, provide rankings of revenues across different auction rules in common value environments. Milgrom and Weber show that the expected revenues from a second-price sealed bid auction are higher than that of a first-price sealed bid auction. Moreover, a special kind of ascending auction, which they fashion after an auction form observed in Japan, yields even higher expected revenues than the second-price auction.

The intuition behind Milgrom and Weber's result is the following: in an environment where bidders signals are affiliated, and valuations are interdependent, observing a higher signal from opponents increases a bidder's valuation of the object, and consequently increases her bid.

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However, in a sealed bid auction, a bidder does not observe anything regarding the information of her opponents, short of their decision to participate (which she might also not observe). In the ascending auction that Milgrom and Weber, however, bidders can observe their opponents bids, and can infer quite a bit about their signals: this is an auction in which price rises continuously, and each bidder has to indicate whether she is in or out of the auction by holding her hand on a button (hence this auction format is sometimes called a "button auction"). Once a bidder releases the button, she drops out of contention, and can not rejoin. Milgrom and Weber show that there exists a symmetric equilibrium in this in which bidders release their buttons in the order of their signals. Thus, a leading bidder can, at least in theory, invert the drop-out decision of her competitors to infer their information completely.

The subtle part of Milgrom and Weber's argument is in showing how more information necessarily translates into higher expected revenues for the auctioneer. In the case of a sealed-bid auction, bidders do not learn anything about the signals of others, therefore they need to rationally lower their bid to prevent the winner's curse. However, in the ascending auction, bidders need not worry about suffering a winner's curse as much – as the auction progresses and people drop out, bidders learn their opponents' valuations of the object. Milgrom and Weber's analysis also suggests the powerful "linkage principle:" the more information is revealed in the auction, the better are the revenue prospects of the auctioneer.

As shown by Ilan Kremer, an ascending auction also has the desirable feature that as the number of bidders becomes large, the selling price of the item converges to its real value – therefore, the auction mechanism prevents the winning bidder to suffer from a large winner's curse. This fact is also intuitively driven by the fact that a much larger amount of information is revealed during an ascending auction as opposed to a sealed bid auction. The winning bidder in an ascending auction with N bidders enjoys the advantage of having observed $N-1$ estimates of the value of the objects, hence the precision of his updated estimate of the object's value is much higher than it would have been in a sealed bid auction.

Empirical support for the information aggregation hypothesis is provided by the recent work of Pai-Ling Yin, who analyzes computer auctions on eBay. She argues that these auctions

might suffer from a winner's curse problem and asks the following question: as the number of bidders in a auction grows, does the auction price converge to the true value of the object? The crux of her analysis is to construct an estimate of the "true value" of the object that is not biased due to the bidders' rational response to alleviate the winner's curse: for each auction in her data set she obtains value estimates from a handful of research assistants, assuming that the research assistants have access to the same conditioning information as the population of the bidders on eBay, and their estimates of the value of the object are unbiased (an assumption that is maintained in models of common value auctions).

Yin finds that as the number of bidders increases, the ratio of auction price to her value estimate approaches one from below. However, even with 20 bidders, the ratio is about 0.8. This points out that if there is a large amount of uncertainty regarding the value of the object, information aggregation is slow.

3.2   Minimum bids

Almost all auction sites on the Internet allow the seller to set a minimum bid (also called a "public" reserve price). This enables the seller to sell the object at a price equal to or higher than her own valuation. Bajari and Hortacsu, for example, observe that the average minimum bid in their sample of collectible coin auctions is 70% of the book value of these coins.

Efficiency requires that sellers set the minimum bid exactly equal to their own valuation of the object. However, this may not be in the seller's best interest. Observe that in an ascending or second-price auction, the minimum binds when it is between the highest and the second highest bids. If the minimum bid is within the support of bidders' valuation distribution, it binds with positive probability. Therefore, even if the seller has zero utility from keeping the object, she has incentive to set a positive minimum bid and prevent some efficient trades from occurring.

In fact, as first discovered by Jeremy Bulow and Paul Klemperer, there is a close connection between monopoly theory and optimal minimum bid setting in private value auctions. To see this connection, we will follow Bulow and Klemperer, and first consider the case where the

auctioneer faces a single bidder, with a private value, v_i, drawn from the distribution $F(v)$ over $[\underline{v}, \bar{v}]$. Assume that the auction is a second price or an ascending auction. If the auctioneer has residual value, v_o, from keeping the object, her expected surplus from selling the object with minimum bid, r, is:

$$(r - v_o)[1 - F(r)]$$

If this objective function is quasi-concave in r, the optimum minimum bid can be calculated through the first-order condition:

$$r = v_o + \frac{1 - F(r)}{f(r)}$$

This expression can be interpreted intuitively as the following: v_o is the marginal cost of the auctioneer, and $\frac{1-F(r)}{f(r)}$ reflects the monopoly mark-up enjoyed by the auctioneer. Observe that the optimal minimum bid is strictly above the auctioneer's valuation of the object. For example, if the distribution of valuations, $F(v)$, is uniform between 0 and $\bar{v}$, and the seller's residual value, v_o, is zero, the optimal minimum bid is $\bar{v}/2$.

What if there is more than one bidder? One might suspect that the "monopoly markup" of the auctioneer might be different when there is tougher competition for the object. It turns out, however, that the identical formula describes the optimal reserve price in this more general case. Observe that, rather remarkably, the above formula does not depend on the number of bidders in the auction. Roughly, this is due to the fact that in a second price auction the minimum bid only has bite when it is between the highest and second highest bids.

Note that the above discussion pertains only to the independent private values case. In the case of common values, the formula for the optimal minimum bid is not known explicitly, but can be calculated numerically if the distribution of the common value, and the distribution of bidders' information regarding the common value (conditional on the realization of the common value) is known.

Another important shortcoming of the theoretical discussion above is that it treats the number of bidders in the auction, N, as being exogenously given. As pointed out by Dan Levin

and James L. Smith, the optimum minimum bid can be very different when bidders must incur a cost to acquire information regarding the object being sold. It is plausible that bidders do incur such a cost before figuring out exactly how much they are willing to pay for the item: before placing a bid, the bidder has to take time to read the auction listing carefully, inspect the seller's feedback profile (which can have hundreds of feedback comments, and require the bidder to click through several pages), and perhaps e-mail the seller with clarifying questions.

Suppose the minimum bid in the auction, as seen by the bidder, is r. Let $\pi(r, N)$ be the bidder's expected surplus from participating in the auction, conditional on there being N bidders. Then the bidder will enter the auction only if $E_N \pi(r, N) \geq c$, her entry cost. If bidders are free to enter the auction, however, the expected surplus enjoyed by bidders will be zero. But then, the seller's revenue from the auction is equal to the social surplus, and the seller's allocation problem (through the choice of the minimum bid) will be aligned with that of a social planner. Therefore, the seller would prefer efficient trades, which she can achieve by setting the minimum bid equal to her own valuation of the object.

Since the presence of entry costs makes an important difference in the efficiency of allocations and in the determination of optimal reserve prices, it is important to determine whether entry costs play a role in the market being analyzed. Online auctions provide a useful testing ground in this respect, given the vast variation in the use of minimum bids across different auctions. A first fact, documented in the studies on eBay coin auctions by Bajari and Hortacsu, and Lucking-Reiley, Bryan, Prasad, and Reeves, is that there is a sharp drop-off in the number of bidders in an auction as the minimum bid increases. However, this does not necessarily reflect the presence of an entry cost – low bids might just not show up in the data due to the minimum bid.

David Lucking-Reiley, in a "field experiment" in which he auctions trading cards for the role-playing game, Magic, tests for the presence of entry costs. He does this by running several simultaneous auctions of different cards with zero minimum bids. He reports that, among the bidders who participated in his auctions, very few bidders placed bids on all of the items he was selling. He argues that this is evidence for the existence of entry costs, since the expected return

from submitting any non-zero bid (not exceeding one's valuation) on these items is positive.

What is the magnitude of these entry costs? Since David Lucking-Reiley's auctions had a 5 cent minimum bid increment, it should at least be 5 cents. Bajari and Hortacsu, in their study of eBay coin auctions, have a different strategy to quantify this cost: assuming that the zero-profit entry condition determines observed participation decisions of bidders, they estimate the implied entry cost of the bidders, using estimated parameters of the bidders' valuation distribution. They find the average entry cost implied by the model to be \$3.20.

One may also use online auction data to test whether observed minimum bid levels are concordant with the theoretical optimum. An obvious problem with performing this test using non-experimental data is the fact that the empirical researcher does not know the seller's residual value. Without this information, the best one can do is to estimate the residual values implied by the observed minimum bids, under the assumption that they are set optimally. One can then check to see if these residual values make sense.

Bajari and Hortaçsu's study verifies, through simulations, that the optimal minimum bid should be equal to the seller's reservation value of the item (since their model is one with common values, this is not an obvious consequence of the theoretical argument above). Since the minimum bids are set, on average, 70% below the book value of the coins in their data set, this implies that sellers' residual values are, on average, 70% of the coins book values. This is rather low if we believe that eBay coin sellers are retailers who have the option of selling these coins to their retail customers, considering book values reflect average retail prices. However, if the outside option of the seller on eBay is to sell to a local coin dealer, then obtaining 70% of book value is not an unrealistic expectation.

David Lucking-Reiley's field experiment using auctions of Magic cards has the advantage in that he is able to change minimum bid levels exogenously. He finds that, contrary to the theoretical prediction, setting a zero minimum bid yields higher revenue than setting the minimum bid equal to its salvage value. His explanation for this finding is that zero minimum bid auctions might possess some extra advertisement value in attracting bidders.

Given the empirical results of Lucking-Reiley and Bajari and Hortacsu, we can conclude

that entry costs play an important role in bidders' participation decisions into Internet auctions. Given this, it is difficult to prescribe the "markup" rule of Myerson, Bulow and Klemperer as an optimum minimum bid strategy. However, it appears that further research into bidders' participation decisions is needed to find the optimal strategy, and to test whether sellers follow this rule.

3.3   Secret reserve prices

In many auctions on the Internet, the seller sets a "reserve price," which is kept secret from the bidders, at least until someone's bid exceeds it. In conventional auction settings, this is also known as "bidding-off-the-wall," where the auctioneer makes up bids as he goes along. The Internet practice is different from this in that the seller commits to the secret reserve price before the auction starts.

Bajari and Hortacsu report that 16% of their sample of coin auctions on eBay were conducted using a secret reserve price. Unfortunately, there has been very little work in the auction theory regarding secret reserve prices, even though they are seen quite frequently in real auction environments. The existence and prevalence of secret reserve prices is somewhat of a mystery in the auction theory literature. This mainly due to the fact that in an independent private values setting, the seller is indifferent between making the reserve price secret or public. So far, the only theoretical explanation is provided by Daniel Vincent's work on affiliated value second price auctions. Vincent's model allows the seller to either set a high minimum bid, or a low minimum bid and a secret reserve price. He then constructs an example in which the secret reserve price can be used to increase the revenue of the seller. The intuition underlying this result is related to the "linkage principle" of Milgrom and Weber: a high minimum bid prevents bidders with low signals from bidding in the auction – this, however, prevents other bidders from learning about the signals of these bidders. This lack of "linkage" can cause bidders with high signals to bid lower, since these bidders might have a greater fear of a winner's curse when they can not infer the signals of the bidders whose would-be bids were censored by the minimum bid.

Bajari and Hortacsu report a second example in which secret reserve prices increase sellers' expected revenue using their estimated structural model of eBay coin auctions. In this example, Bajari and Hortacsu compare the expected revenues predicted by their model under two cases: in the first case, the seller sets the (optimal) minimum bid equal to her salvage value of the coin, and in the second case, she sets a zero minimum bid and a secret reserve price equal to her salvage value. They find that for coin with a book value of $60, setting a secret reserve price increases the expected revenue by about 50 cents. For a $200 coin, using a secret reserve price yields about $2 more in revenue.

Somewhat different results are obtained by Rama Katkar and David Lucking-Reiley who conduct an interesting "field experiment" to compare the revenue performance of secret reserve prices and minimum bids. In this experiment, Katkar and Lucking-Reiley bought 50 matched pairs of collectible Pokemon cards, and set up auctions on eBay to sell these cards. To be able to generate "treatment" and "control" groups, Katkar and Lucking-Reiley auctioned one card in each pair with a minimum bid, and the other with a secret reserve that was set equal to the minimum bid.

This experiment resulted in auctions with a secret reserve price generating about 60 cents revenue on average (average card value was $6.80 in one experimental run and $7.50 in the other). Katkar and Lucking-Reiley conclude that this is evidence that secret reserve prices could be used for reasons other than maximizing revenues on eBay. Their alternative explanation is that some sellers may use very high secret reserve prices to elicit the willingness to pay of auction participants, and after the auction is completed, send an e-mail to the bidder with the highest bid to make a take-it-or-leave-it offer. This strategy allows the seller to avoid paying eBay a commission on the sale, and possibly extract a higher price than the second highest bid in the auction. This explanation is also consistent with the finding in Bajari and Hortacsu that higher value objects were more likely to be sold using a secret reserve price. eBay's commission on high-value objects can be quite significant, so the seller might prefer to sell the item outside of eBay after having learned the "demand curve" for the object.

Before we conclude that secret reserve prices are, in general, a bad idea for sellers who

do not partake in "gray-market" activities, we should point out that the experimental design of Katkar and Lucking-Reiley is not ideal to answer this question. To answer this question, the comparison should be made between the "optimal" minimum bid and the "optimal" secret reserve price that could have been set by a seller. Also, as Katkar and Lucking-Reiley point out, their results are obtained for low book value items (around $7); it could very well be that secret reserve prices play a revenue enhancing role for higher value auctions.

4 Conclusion

Online auctions are one of the most successful and exciting innovations of the New Economy. Online auction sites like eBay, Yahoo and Amazon have introduced millions of people to the joys and dangers of bidding. These sites are also great sources of data for economists who want to test theories of strategic behavior in auctions. Insights from these empirical tests can be used to improve the design of auction mechanisms on the Internet and elsewhere.

The main insights from the very new but rapidly growing empirical literature on online auctions are the following:

1. Informational asymmetries play an important role in online auctions. The reputation mechanism used by eBay to reduce the informational asymmetry between buyers and sellers appears to be working well – the market appears to have settled to a steady state in which only "good" sellers are active. Informational asymmetries between buyers, i.e. the "winner's curse," also appears to play an important role, since a large fraction of goods bought and sold on online auctions are collectibles, which are bought primarily for their (uncertain) resale value.

2. Ascending auctions are the most popular auction mechanisms in use. This auction format has distinct advantages in terms of reducing coordination and cognitive costs for bidders, in reducing the winner's curse, and in achieving efficient information aggregation. However, subtle changes in auction rules, such as imposing a fixed deadline as opposed to a "going-going-gone" rule has profound influence on bidder behavior. This points out

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the "strategic complexity" of dynamic auction formats as opposed to static, sealed-bid formats, and opens the way for further theoretical and empirical research.

3. Bidders face non-zero decision and/or bidding costs on Internet auctions. The existence of such costs affects optimal seller responses regarding the choice of minimum bid levels and the use of reserve prices, which, in turn, affect the price formation process and the efficiency of the allocations. Given that entry costs play an important role on a relatively "frictionless" medium like the Internet, economists designing markets in other environments should attempt to quantify these costs, and incorporate them into their models.

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Figure 1

item view

6 MORGAN SILVER DOLLARS "NR"

Item # 1320292746

Coins:Coins: US:Dollars:Morgan (1878-1921)

Coins:Coins: US:Collections, Lots

Currently	**$59.01**	First bid	**$1.00**
Quantity	**1**	# of bids	**17** bid history
Time left	**10 mins, 0 secs**	Location	**HOME OF THE COLTS**
		Country/Region	**USA/Indianapolis**
Started	Jan-09-02 15:36:26 PST	mail this auction to a friend	
Ends	Jan-16-02 15:36:26 PST	watch this item	

Seller (Rating) **geno_coins (26)** ⭐

view comments in seller's Feedback Profile | view seller's other auctions | ask seller a question

High bid **92240 (29)** ⭐

Payment Money Order/Cashiers Checks.

Shipping Buyer pays fixed shipping charges. Will ship to United States only.

Seller assumes all responsibility for listing this item. You should contact the seller to resolve any questions before bidding. Auction currency is U.S. dollars ($) unless otherwise noted.

Description

You are bidding on 6 morgan silver dollars ,dates are 1921P,D,S, 1884-O, 1885, 1899-O I'll make this a true auction and start the bid at $1.00 with "NR" . $5.00 covers S/H plus $1.10 for insurance if wanted. Coins grade from VF to AU . Happy Bidding

00210

Free **Honesty** Counters powered by Andale!

Payment Details		**Payment Instructions**
U.S. Shipping and Handling	$5.00	MONEY ORDERS AND CASHIERS CHECKS ONLY PLEASE
Shipping Insurance per item (optional)	$1.10	
Sales Tax (none)		

Learn more about checkout

Bidding

6 MORGAN SILVER DOLLARS "NR"
Item # 1320292746

Current bid:	$59.01
Bid increment:	$1.00

Your maximum bid: [   ]

(Minimum bid: $60.01)

[Review bid]

eBay will bid incrementally on your behalf **up to your maximum bid** , which is kept secret from other eBay users. The eBay term for this is proxy bidding .

Your bid is a contract - Place a bid only if you're serious about buying the item. If you are the winning bidder, you will enter into a legally binding contract to purchase the item from the seller.

How to Bid

1. Register to bid - if you haven't already. It's free!

2. Learn about this seller - read feedback comments left by others.

3. Know the details - read the item description and payment & shipping terms closely.

4. If you have questions - contact the seller geno_coins *before* you bid.

5. Place your bid!

eBay purchases are insured .