Journal of Economic Literature
Vol. XLII (June 2004) pp. 457–486

Economic Insights from Internet Auctions

PATRICK BAJARI *and* ALI HORTAÇSU[1]

1. *Introduction*

Electronic commerce continues to grow at an impressive pace despite widely publicized failures by prominent online retailers. According to the Department of Commerce, total retail e-commerce in the United States in 2002 exceeded $45 billion, a 27-percent increase over the previous year. Online auctions are one of the most successful forms of electronic commerce. In 2002, more than 632 million items were listed for sale on the web behemoth eBay alone, a 51-percent increase over the previous year. This generated gross merchandise sales of more than $15 billion.

The rapid development of these markets is usually attributed to three factors.[2] The first is that online auctions provide a less-costly way for buyers and sellers on locally thin markets, such as specialized collectibles, to meet. Adam Cohen (2002, p. 45) states, "It would be an exaggeration to say that eBay was built on Beanie Babies, but not by much."[3] In May 1997, nearly $500,000 worth of Beanie Babies was sold on eBay, totaling 6.6 percent of overall sales. While it may be difficult to find a particular Beanie Baby locally, such as Splash the Whale or Chocolate the Moose, you have a good chance of finding it online. Collectibles such as Beanie Babies, first edition books, Golden Age comics, and Elvis paraphernalia are among the thousands of categories actively traded in online auctions.

The second factor is that online auction sites substitute for more traditional market intermediaries such as specialty dealers in antiques, sports cards, and other collectibles. For instance, an antique dealer from Seattle explained on an eBay message board why he closed his store:

> A couple of years or so ago my best buyers started spending their money at eBay. Then my pickers started selling on eBay instead of selling to me. Then when I went to the flea market and asked how much an item was, I got quoted what

[1] Bajari: Duke University and NBER. Hortacsu: University of Chicago and NBER. We thank the editor, two anonymous referees, Ginger Jin, Axel Ockenfels, David Reiley, Paul Resnick, and Alvin Roth for their very detailed and insightful comments on various drafts of this document. We thank the National Science Foundation for partial research support, grants SES-0012106 (Bajari) and SES-0242031 (Hortaçsu).

[2] There are several interesting accounts of the early development of internet auctions. Cohen (2002) chronicles the development of eBay through in-depth interviews of eBay founders, executives, and users. David Lucking-Reiley (2000b) provides an insightful description of internet auction sites and auction mechanisms across different market segments.

[3] Beanie Babies are stuffed dolls that are popular among collectors.

> one sold for on eBay, not what the seller wanted for the item. I have a toy show that sold out for years, but nowadays all my vendors sell on eBay, and all the buyers are spending their money on eBay. I used to buy and sell a lot in the toy magazines before they got reduced to mere pamphlet-sized rags… Get my drift? (Cohen, p. 110)

Online auctions have extensive listings and powerful search technologies that create liquid markets for specialized product categories. The resulting reduction in transaction costs forced some intermediaries, like the antique dealer above, to exit the market.

Finally, online auctions can be fun! Many bidders clearly enjoy contemplating the subtleties of strategic bidding and sharing their insights with others. Most online auction sites have active message boards where one can learn the fine points of collecting. The boards also provide a sense of community for diehard collectors.

In this paper, we survey recent research concerning online auctions. First, we describe the mechanics of the auction rules used on the most popular sites and some empirical regularities. An especially interesting regularity is that bidders frequently snipe; that is, they strategically submit their bids at the last seconds of an auction that lasts several days. Several authors have empirically examined sniping and proposed explanations.

We then survey a growing literature in which researchers have attempted to document and quantify distortions from asymmetric information in online auction markets. As pointed out by Eichiro Kazumori and John McMillan (2003), the "information asymmetry" problem constitutes perhaps the biggest limitation posed to the impressive growth of online auctions. In online auctions, transactions take place between complete strangers who may not live in the same state or the same country, making it very difficult for buyers to directly inspect the good or to make sure that the good will be delivered at all. This creates opportunities for misrepresentation of objects and fraudulent behavior by sellers, which may limit trade in these markets.[4]

The informational asymmetry may manifest itself as a "winner's curse" problem, in which bidders recognize that winning an auction is conditional on being the most optimistic bidder about the item's worth. Auction theory then predicts that bidders will respond strategically to the winner's curse by lowering their bids, thus leading to lower prices and volumes in these markets. In section 4, we will survey empirical work that uses detailed data from online auction sites to test whether bidders indeed act strategically in the face of a possible winner's curse, and whether this strategic response is large enough to prevent fraudulent sellers from extracting (short-term) rents.

Given the above discussion, a very important component of the online auction business is to decrease the informational asymmetries between market participants. A particularly popular method, pioneered by eBay, is the use of feedback mechanisms that allow buyers and sellers to leave publicly available comments about each other. In section 5, we will survey a rapidly growing empirical literature that utilizes data from the feedback mechanisms of online auction sites to quantify the market value of online reputations.[5]

Auction theory, with its sharp predictions about the optimal way to design and conduct auctions, has become one of the most successful and applicable branches of microeconomic theory. Internet auction sites, with their abundance of detailed data on bidding and selling behavior, provide

[4] A number of high-profile incidents of fraud have occurred on online auctions. For instance, the FBI launched an investigation called "Operation Bullpen" that led to the indictment of 25 persons for selling tens of millions of dollars of forged collectibles such as forged signatures from Babe Ruth and Lou Gehrig (Cohen, p. 308).

[5] Another survey article that provides a more in-depth survey of theoretical models of reputation is Chrysanthos Dellarocas (2002). See also the survey by David Baron (2002).

fertile ground to test some of these theories. On many internet auction sites, sellers are allowed to fine-tune their auctions by experimenting with minimum bids or secret reserve prices. Several sites also allow the sellers to make choices regarding which auction format to use. Thus, empirical researchers can utilize these sources of variation, along with a newfound ability to set up randomized "field experiments" to test predictions of auction theory. In section 6, we discuss several strands of research addressing this purpose. We first discuss the use of internet auction sites as a medium for randomized field experiments, and survey empirical work that has utilized this methodology to compare bidder behavior across alternative auction formats. Second, we discuss the use of both field experimentation and structural econometric modeling techniques to investigate how sellers should set reserve prices for their auctions. In particular, we focus on the question of why reserve prices are kept secret in many internet auctions. Third, we discuss the prevalence of ascending auctions on the internet. We consider alternative theoretical explanations, along with a discussion of new experimental evidence motivated by this empirical observation. Finally, we discuss the importance of taking endogenous participation decisions into account when conducting theoretical and empirical comparisons of different auction rules, since online auction sites typically feature multiple auctions that are taking place at the same time (and the sites themselves can be thought of as competing with each other through their site designs). We conclude with a brief discussion of open research questions that remain to be explored.

2. *Buying and Selling in Online Auctions*

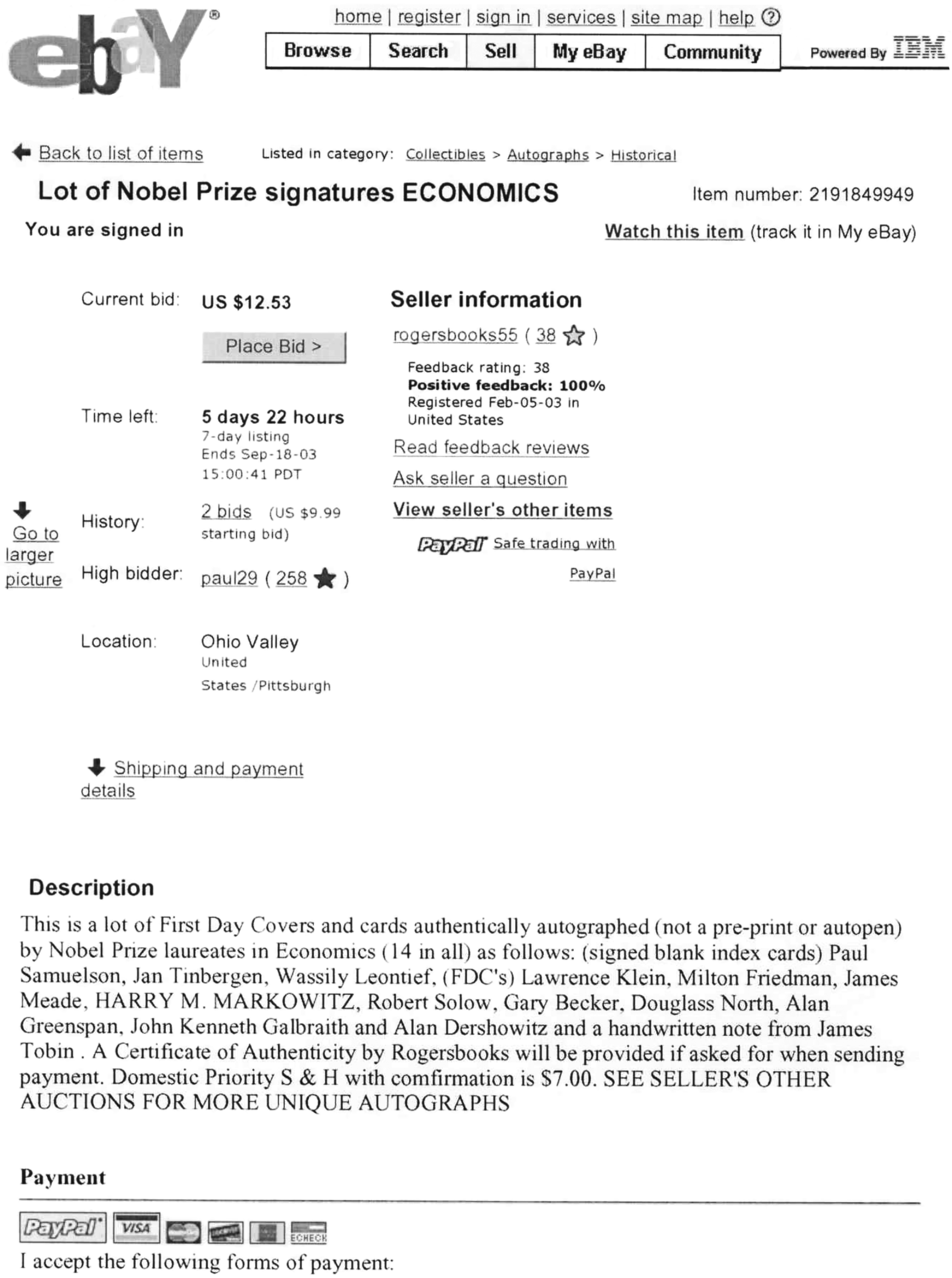
On any given day, sellers list millions of items in online auctions. These sites include business-to-business (B2B) sites,[6] and sites where the typical buyer is a consumer. We will focus on the latter category since this has been the focus of most empirical research. On the largest sites, such as eBay, Amazon, and Yahoo!, bidders can choose from a mind-boggling array of listings.[7]

These sites facilitate search in two ways. First, the sites have a carefully designed set of categories and subcategories to organize the listings. For instance, eBay's main page lists general categories that include automobiles, real estate, art, antiques, collectibles, books, and music. Within a subcategory, there are multiple layers of additional categories. For instance, the subcategory of paintings includes antique American and modern European. These categories are carefully designed by the auction site to facilitate buyers' searches. Secondly, users can search the millions of listings by keywords, category, price range, and completed items. This allows users to gather considerable information about similar products, which is useful in forming a bid.

In figure 1, we display a listing from eBay. The web page describes the item for sale, which in this case is a collection of signatures of fourteen Nobel laureates in economics. The user can see the current high bid, the time left in the auction, the identity of the seller, and the highest bidder. The web page describes the item for sale and

[6] See David Lucking-Reiley and Daniel Spulber (2001). Examples are MuniAuction.com, which conducts auctions of municipal bonds; ChemConnect.com for trade in chemicals; Wexch.com for electricity contracts.

[7] Lucking-Reiley (2000b) surveyed 142 online auction sites that were in operation in autumn of 1998. Exact estimates of the number of auction listings are few and far between. Lucking-Reiley (2000b) reported that in summer 1999, 340,000 auctions closed on eBay every day, as opposed to 88,000 on Yahoo!, and 10,000 on Amazon (most auctions last seven days). Sangin Park (2002) reports, based on Nielsen/NetRatings surveys that eBay had 5.6 million listings, and Yahoo!, 4.0 million listings as of autumn 2000. When we counted the number of active listings on January 25, 2004, we found 14.5 million listings on eBay, and only 193,800 listings on Yahoo!. Our counts of Amazon listings were much more inexact, since the website does not divulge this information as visibly as eBay or Yahoo!. However, our estimate is between 500,000 and 1.5 million listings.



home | register | sign in | services | site map | help

Browse | Search | Sell | My eBay | Community

Powered By IBM

Back to list of items

Listed in category: Collectibles > Autographs > Historical

Lot of Nobel Prize signatures ECONOMICS

Item number: 2191849949

You are signed in

Watch this item (track it in My eBay)

Current bid: **US $12.53**

Place Bid >

Time left: **5 days 22 hours**
7-day listing
Ends Sep-18-03
15:00:41 PDT

Go to larger picture

History: 2 bids (US $9.99 starting bid)

High bidder: paul29 (258)

Location: Ohio Valley
United
States /Pittsburgh

Shipping and payment details

Seller information

rogersbooks55 (38)

Feedback rating: 38
Positive feedback: 100%
Registered Feb-05-03 in
United States

Read feedback reviews

Ask seller a question

View seller's other items

PayPal Safe trading with PayPal

Description

This is a lot of First Day Covers and cards authentically autographed (not a pre-print or autopen) by Nobel Prize laureates in Economics (14 in all) as follows: (signed blank index cards) Paul Samuelson, Jan Tinbergen, Wassily Leontief, (FDC's) Lawrence Klein, Milton Friedman, James Meade, HARRY M. MARKOWITZ, Robert Solow, Gary Becker, Douglass North, Alan Greenspan, John Kenneth Galbraith and Alan Dershowitz and a handwritten note from James Tobin . A Certificate of Authenticity by Rogersbooks will be provided if asked for when sending payment. Domestic Priority S & H with comfirmation is $7.00. SEE SELLER'S OTHER AUCTIONS FOR MORE UNIQUE AUTOGRAPHS

Payment

PayPal VISA ECHECK

I accept the following forms of payment:

Figure 1. Sample eBay Listing

sometimes displays a seller-supplied picture. The listing also displays the seller's feedback to the right of the seller's identity. Users on eBay can leave each other feedback in the form of positive, neutral, or negative comments. The total feedback is the sum of positive comments minus the number of negative comments. eBay also computes the fraction of positive feedback received by the seller.[8]

The listing displays the minimum bid and whether the seller is using a secret reserve. The minimum bid is analogous to a reserve price in auction theory; that is, the seller will not release the item for less than the minimum bid. A secret reserve price functions similarly except that it is not publicly displayed to the bidders. Bidders can only see whether or not the secret reserve is met. Sellers on eBay pay an insertion fee and a final value fee. The insertion fee is based on the minimum bid set by the seller. For instance, if the minimum bid is between \$25 and \$50, the insertion fee is currently \$1.10. The final sale fee is a nonlinear function of the final sale price. For items with a final sale price of less than \$25, the fee is 5.25 percent of the final sale price. Higher sale prices are discounted at the margin. Also, eBay has additional fees if a secret reserve is used or if more than one picture is used.[9]

At the bottom of the listing, buyers can submit their bids. All three major online auction sites use some variant of proxy bidding.[10] Here's how it works. Suppose that a seller lists an Indian-head penny for sale with a minimum bid of \$15.00. At this price level, eBay requires a bid increment of \$.50 to outbid a competitor.[11] If bidder A places a proxy bid of \$20, the eBay computer will submit a bid of \$15.00, just enough to make bidder A the highest bidder. Suppose that bidder B comes along and submits a bid of \$18.00. Then the eBay computer will update A's bid to \$18.50 (the second-highest bid plus one bid increment). The proxy bidding system updates A's bid automatically, until A is outbid by another bidder. If this occurs, the bidder will be notified by email and given a chance to update their bid.

Although all three sites use the proxy-bidding mechanism, they differ in how they end the auction. eBay auctions have a fixed ending time set by the seller, who chooses a duration between one, three, five, seven, and ten days, and the auction closes exactly after this duration has passed.[12] On Amazon, if a bid is submitted within the last ten minutes of the previously fixed ending time, the auction is automatically extended for ten additional minutes. Furthermore, for every subsequent bid, the ten-minute extension still applies. Hence, the auction ends only if there is no bidding activity within the last ten minutes. Interestingly, Yahoo! takes the middle-ground between these two ending rules, and allows sellers to choose which one to apply to their auction. As we will see in the next section, this seemingly innocuous difference in ending rules is associated with divergent bidding behaviors across auction sites.

3. *Last-Minute Bidding*

Bids commonly arrive during the last seconds of an internet auction that lasts as long as several days. For instance, Alvin Roth and Axel Ockenfels (2002) and Ockenfels and Roth (2003) find, in a sample of 240

[8] Similar mechanisms are used on Yahoo! and Amazon. Yahoo!'s feedback pages look almost exactly like eBay's. Amazon uses a slightly different five-star system to summarize the comments.

[9] The fees that eBay charges have been updated several times, with vocal dissent from eBay sellers in certain instances, such as when eBay decided to charge a \$1 fee to use the secret reserve option (Troy Wolverton 1999). Also, see Park (2002) for some evidence on the impact of network effects on the competition (in listing-fees) between eBay and Yahoo!

[10] Yahoo! also allows "straight bidding," i.e., bidding precisely the price you want to pay.

[11] eBay has a sliding scale of bid increments, based on the current price level in an auction.

[12] There is a 10-cent charge for running a ten-day auction on eBay.

antique auctions on eBay, that 89 had bids in the last minute and 29 in the last ten seconds. Other researchers, including Ronald Wilcox (2000), Bajari and Hortaçsu (2003), and Julia Schindler (2003), have documented similar patterns. In this section, we summarize some of the proposed explanations for last-minute bidding and the related empirical work.

Last-minute bidding is difficult to explain using standard auction theory. Proxy bidding bears a strong similarity to the second-price sealed-bid auctions since, in both cases, the payment by the winning bidder is equal to the second highest bid. William Vickrey (1961) observed that in a second-price sealed-bid auction with private values, it is a weakly dominant strategy for a bidder to bid their reservation value. The intuition is simple. If the bid is less than their private value, there is a probability that she will lose the auction. However, the payment the winning bidder makes only depends on the second-highest bid. As a result, bidding one's valuation weakly increases one's payoff. Thus, at first glance, it appears that bidders can leave their proxy agents to do their bidding, and do not need to wait until the last seconds of the auction.

However, this is clearly not what happens in practice, and therefore several explanations for late bidding have been proposed in the literature. A first explanation, which departs only slightly from the independent private values environment, is proposed by Ockenfels and Roth (2003). They argue that late bidding may be a form of "tacit collusion" by the bidders against the seller. In their model, bidders can choose to bid early or late. A late bid, however, might not be successfully transmitted due to network traffic. There are (at least) two possible equilibria in their model. In the first, agents bid early in the auction, and in the second agents only bid at the last second. Bidding late is a risk because the bids may not be successfully transmitted. On the other hand, late bidding softens competition compared to the first equilibrium.

Ockenfels and Roth (2003) demonstrate that this "tacit collusion" explanation of last-minute bidding equilibrium hinges on the assumption that there is a hard deadline for submitting bids. As mentioned in the last section, however, while eBay auctions have a hard deadline, Amazon auctions are automatically extended if a late bid arrives. Ockenfels and Roth (2003) then demonstrate that late bidding is no longer an equilibrium in Amazon-style auctions. They conclude that there are more powerful incentives for late bidding in eBay auctions than in Amazon auctions.

As a test of this theory, Roth and Ockenfels (2002) and Ockenfels and Roth (2003) compare the timing of bids for computers and antiques on Amazon and eBay. They find that late bidding appears to be more prevalent in the eBay auctions. On eBay, bids are submitted within the last five minutes in 9 percent of the computer auctions and 16 percent of the antique auctions. On Amazon, about 1 percent of the auctions in these categories receive bids in the last five minutes. Bidder surveys reveal that late bidding on eBay is a deliberate strategy meant to avoid a bidding war. Similar evidence comes from Schindler (2003), who studies bidding in Yahoo auctions for computers, art, and cars. In these auctions, the sellers can choose to have a hard close or an automatic extension, similar to Amazon auctions, if late bids arrive. She finds that, consistent with the Ockenfels and Roth theory, the winning bidder tends to arrive later in the auctions, with a hard ending for all three product categories.

We should note that the empirical finding by Roth and Ockenfels (2002), Ockenfels and Roth (2003), and Schindler (2003)—that there is less sniping in flexible-ending rule auctions—is not confirmed in all studies. Gillian Ku, Deepak Malhotra, and J. Keith Murnighan (2003) study bidding in online auctions in several U.S. cities for art that has been publicly displayed. The proceeds of the auctions were donated in part to charitable causes. The authors observe online auctions with both hard endings and flexible endings. They observe substantially less late bidding than the previously mentioned studies. Only 1.6 percent of the bids arrive in the last five minutes of the auctions with hard deadlines and 0.5 percent in the auctions with flexible endings. Also, Ku et al. find that for auctions with flexible endings, a greater percentage of the bids arrive in the last hour and the last day than for auctions with hard endings. This is not qualitatively consistent with Ockenfels and Roth's prediction. However, it is important to note that the authors have limited controls for heterogeneity across auctions that are held in different cities.

Several other empirical researchers have examined the tacit collusion hypothesis of Ockenfels and Roth further. Kevin Hasker, Raul Gonzalez, and Robin Sickles (2003) test the Ockenfels and Roth theory by examining bids for computer monitors on eBay. If late bids soften competition and lower the probability of price wars, then the distribution of the winning bids conditional upon a snipe should not equal the distribution of the winning bids if no snipe occurs. Hasker et al. find that in most of the specifications they examine, they are unable to reject the equality of these two distributions. They argue that this is inconsistent with the "tacit collusion" theory. Similarly, in a data set of bidding for eBay coin auctions, Bajari and Hortaçsu (2003) find that reduced form regressions suggest that early bidding activity is not correlated with increased final sales prices. Schindler's (2003) study also casts some doubt on the tacit collusion hypothesis on the revenue front. Under private values, the Ockenfels and Roth model predicts that a hard close will decrease revenues for the seller.[13] Schindler finds sellers more frequently use auctions with automatic extensions for art (82 percent vs. 18 percent), and cars (73 percent vs. 27 percent), but not for computers (91 percent vs. 9 percent). Therefore, under the Ockenfels and Roth theory, the first two categories are consistent with seller revenue maximization while the last category is not.

A second theoretical explanation, also offered by Ockenfels and Roth (2003) is the presence of naïve bidders on eBay who do not understand the proxy-bidding mechanism, and hence bid incrementally in response to competitors' bids.[14] Ockenfels and Roth (2003) demonstrate that last-minute bidding is a best-response by rational bidders against such naïve bidders. They present empirical evidence that more experienced bidders are less likely to place multiple, incremental bids on eBay. This evidence is complemented by survey evidence reported in Roth and Ockenfels (2002). Furthermore, Dan Ariely, Ockenfels, and Roth (2003) conduct a controlled laboratory experiment in which one of the experimental treatments is an eBay-type fixed-deadline auction, where the probability of "losing" a bid due to transmission error is zero. Notice that this feature rules out the tacit collusion explanation; however, it is still a best-response against naïve incremental bidders to bid at the last second. Accordingly, Ariely et al. (2003) find a significant amount of late-bidding activity in this experimental treatment.

A third explanation is based on a common value. In a common-value auction, such as Robert Wilson's (1977) mineral-rights model, the item up for sale has a true value V that is not directly observed by the bidders. For example, the common value V could be the resale value of a collectible. Each bidder receives an imperfect signal x of V which is private information. By bidding early, a bidder may signal information about x to other bidders and cause them to update their

[13] However, this revenue ranking may be reversed in an affiliated interdependent values environment.

[14] Based on survey data, Ku et al. (2003) also find that some bidders may be driven by emotional factors, which they label as "competitive arousal." For instance, one survey respondent from Cincinnati who purchased a ceramic pig explained that she "really wanted the pig, and probably also got caught up in the competitive nature of the auction." Another respondent explained her behavior by stating, "Auction fever took over."

beliefs about V. Conditional on winning, this may increase the price that a bidder has to pay for the item. Bajari and Hortaçsu (2003) formalize this intuition and demonstrate that last-minute bidding occurs in models of online auctions with a common value—in fact, they show that in a symmetric common-value environment, the eBay auction can be modeled as a sealed-bid second-price auction. A similar result is also provided in Ockenfels and Roth (2003) in a simpler setting. This explanation also finds some support in the data. Roth and Ockenfels (2002) and Ockenfels and Roth (2003) report that there is more last-minute bidding on eBay antiques auctions than in eBay computer auctions. They argue that antiques auctions are more likely to possess a common value element than computer auctions, and hence the observed pattern is consistent with the theoretical prediction.

A fourth explanation for late bidding is proposed by Joseph Wang (2003), who studies a model in which identical items are simultaneously listed, as opposed to the usual assumption that only a single unit of the item is up for sale. Last-minute bidding is part of the unique equilibrium to his model. Michael Peters and Sergei Severinov (2001) argue that their model of bidding for simultaneous listings of identical objects is also qualitatively consistent with late bidding. Taken together, these two papers suggest that the multiplicity of listings is another explanation for late bidding. However, it is not clear whether the Wang (2003) and Peters and Severinov (2001) models predict that last-minute bidding should be less prevalent on Amazon as opposed to eBay.

A fifth explanation is given by Eric Rasmusen (2001), who considers a model in which bidders have uncertainty about their private valuation for an item. As in the model of Dan Levin and James Smith (1994), he assumes that some bidders must pay a fixed fee to learn their private information. This is not an unreasonable assumption in online auctions. In order to learn their private valuations, bidders will inspect the item and may search for sales prices of previously listed items. The fixed fee can be thought of as the opportunity cost of time required to do this research. Rasmusen demonstrates that late bidding can occur because bidders wish to economize on the costs of acquiring information.

The multiplicity of explanations provided in the literature regarding the causes of a seemingly innocuous phenomenon like last-minute bidding is a great example of how the analysis of online auctions enables us to appreciate the richness and complexity of strategic interaction in markets. The preceding discussion also illustrates how a seemingly simple empirical regularity can have multiple explanations, and that it is not easy to discern between these explanations without creative exploitation of sources of variation in the data. In this regard, the experimental study of Ariely, Ockenfels, and Roth (2003) is a good demonstration of how laboratory experiments can complement data obtained from real markets to help explain complex strategic interactions.

4. *The Winner's Curse*

In online markets, buyers are not able to perfectly observe the characteristics of the goods for sale. In the market for collectibles and other used goods, buyers value objects that appear new. Scratches, blemishes, and other damage will lower collectors' valuations. Since a buyer cannot directly touch or see the object over the internet, it may be hard to assess its condition. This introduces a common-value component into the auction, and therefore bidders should account for the winner's curse.

The winner's curse can be illustrated by the following experiment discussed in Peter Coy (2000):

> Paul Klemperer … illustrates the winner's curse to his students by auctioning off a jar with an undisclosed number of pennies. The students bid a little below their estimate of the jar's contents to leave a profit. Every time,

though, the hapless winner of the jar is the student who overestimates the number of pennies by the greatest amount, and therefore overpays by the most.

The winner's curse occurs when bidders do not condition on the fact that they will only win the auction when they have the highest estimate. If there is a large number of bidders, the highest estimate may be much larger than the average estimate. Therefore, if the winner bids naively, he may overpay for the item. In addition to the classroom experiment above, a number of experimental studies find that inexperienced bidders frequently are subject to the winner's curse (see John Kagel and Alvin Roth 1995 for a survey of the experimental literature).

Several authors empirically examine whether bidders are subject to the winner's curse and, more generally, measure distortions from asymmetric information in online markets. Two main methodologies have been utilized to answer this question so far. The first method, utilized by Ginger Jin and Andrew Kato (2002), is to sample goods in an actual market, and determine whether the prices reflect the ex-post quality of the goods they buy. Online auctions present perhaps a unique opportunity in the utilization of this methodology, since items sold in these markets are inexpensive enough to allow researchers to "shop" out of their own pockets or research grants.

In particular, Jin and Kato (2002) study fraudulent seller behavior in an internet market for baseball cards. Fraud on the internet is a problem. The Internet Fraud Center states that 48 percent of the 16,775 complaints lodged in 2001 were from online auctions. In this market, Jin and Kato find that sellers frequently misrepresent how baseball cards will be graded.

Professional grading services are commonly used for baseball cards. Grading services produce a ranking from 1 to 10 based on the condition of the card. Cards that are scratched or have bent corners are assigned lower grades than cards that are in mint condition. Jin and Kato bid on eBay auctions for ungraded cards and then submitted the cards to a professional grading service.[15] Their sample contained 100 ungraded baseball cards. Of these, sellers of nineteen claimed that they had a ranking of 10 (gem mint), 47 claimed mint (9 or 9.5), sixteen near-mint to mint (8 or 8.5), seven near-mint (7 or 7,5); eleven cards had no claim.

Many sellers of ungraded cards misrepresented the card quality. Among sellers who claimed that their cards were grade 9 to 10, the average grade was 6.34. In comparison, the average grade of cards claiming 8.5 or below was 6.87. The price difference between a grade 10 and a grade 6.5 for some cards could be hundreds or thousands of dollars. Jin and Kato find evidence that some buyers were misled by these claims. Buyers were willing to pay 27 percent more for cards that were seller-reported as 9 to 9.5 and 47 percent more for cards that were reported as 10. They conclude that some buyers have underestimated the probability of fraud and therefore have fallen prey to the "winner's curse."

To establish whether the winner's curse problem is more of an issue in online as opposed to offline markets, the authors employed male agents between 25–35 years of age to purchase the same types of cards from retail collectibles stores in eleven metropolitan districts, and found that the fraud rate there (3.2 percent) was much lower than online (11 percent). Moreover, in their retail purchases, the authors found that retail sellers were more reluctant to quote the likely grade of the cards when one was not available.

Does this mean that online auctions for baseball cards are fraught with fraudulent sellers and naïve buyers—a market that could use further regulation and intervention by third parties to operate more efficiently?

[15] They attempted to bid just enough to win the auction and to have a minimal effect on the actions of other players.

Before we jump to this conclusion, we believe that a cautious interpretation of Jin and Kato's findings is in order. In our opinion, the main finding of this paper is that "while online bidders account for the possibility of misrepresentation, they might make mistakes when assessing the probability of fraudulent claims." It should be pointed out that the "mistakes" that buyers make are not likely to lead to very large monetary losses, since most items in this market are mundanely priced (between $60 and $150). Even for more valuable items, the estimated losses from buyer naivete are not very large. For instance, Jin and Kato report that the average eBay price for a grade-10 Ken Griffey Jr.'s 1989 Upper Deck Card (the most actively traded card on eBay) is $1,450. An ungraded Griffey with a self-claim of 10 only sold for an average of $94.26. Jin and Kato's estimates imply that this self claim generated an extra $30 in revenue for a fraudulent seller. If bidders naively took the claims at face value, this would have generated a mistake of over $1,300—hence the Ken Griffey example shows that bidders by and large do correct for the winner's curse. The contention is whether the bidders correct enough for this. Furthermore, the authors did manage to purchase a card of mint quality (grade 9) from their ungraded group. Apparently, taking a chance with ungraded cards sometimes does in fact pay off.

Regardless of how one may interpret Jin and Kato's (2002) findings, their methodology to assess the prevalence of fraud and the magnitude of the corresponding "winner's curse" suffered by buyers is a very direct and effective way to get precise measurements. Unfortunately it would be difficult, if only due to budget constraints, to replicate this methodology to examine markets for more expensive items like computers or automobiles (which are actively traded on eBay). Hence, the second set of papers we will survey utilizes more "indirect" methods that rely on testing the implications of strategic bidding in common-value auction models (in which bidders account for the presence of a winner's curse.)

The first study we will summarize in this regard is Bajari and Hortaçsu (2003), who examine the effect of a common value on bidding for collectible coins in eBay auctions. The authors first argue that bidding in an eBay auction in the presence of a common-value element can be modeled as bidding in a second-price sealed-bid auction with common values (and an uncertain number of opponents). The reasoning is based on the observation of sniping in these auctions: the presence of a common-value element in an eBay auction suggests that bidders should wait until the last minute in order to avoid revealing their private information. If all bids arrive at the last minute, a bidder will not be able to update his beliefs about the common value V using the bids of others—hence his bidding decision will be equivalent to that of a bidder in a sealed-bid second-price auction.

Given this argument, the authors then test for the presence of a common-value element using an idea first proposed by Harry Paarsch (1992).[16] If the auction environment is one with purely private values, it is a dominant strategy for bidders to bid their private values, independent of the number of competitors that they face. If there is a common-value element, however, the bids will depend on the number of bidders present. This is because when there are more bidders, the possibility of suffering a winner's curse conditional on winning the auction is greater, further cautioning the bidders to temper their bids to avoid the curse.

Bajari and Hortaçsu (2003) implement this using cross-sectional regressions of bids on the number of bidders, and apply various

[16] We should note, however, that Paarsch (1992) implemented his idea in the context of first-price auction, where the comparative static with respect to the number of bidders in the auction is ambiguous. See Susan Athey and Philip Haile (2002) and Haile, Han Hong, and Matthew Shum (2003) for more rigorous derivations of this comparative static result in the context of second-price and ascending (button) auctions.

instruments to account for the endogeneity of the number of bidders in the auction. Consistent with the presence of a common-value element, they find that bids decline with the number of competing bidders. They test whether bidders with little eBay experience tend to bid systematically higher, by regressing individual bids on total eBay feedback. While they find a statistically significant effect on bids, it is very small in magnitude. This is not consistent with experimental evidence that suggests inexperienced participants overbid, and hence are more likely to suffer from a winner's curse.

Next, the authors attempt to directly measure the distortions from asymmetric information by estimating a structural model. In their structural model, the data generating process is a Bayes-Nash equilibrium where: 1) there is a common value, 2) bidders have to pay a fixed cost to learn their signal x, and 3) entry is endogenously determined by a zero profit condition. Given this structural model, they estimate the parameters for the distribution of the common value V, the distribution of bidder's private information, x and the parameters that govern entry decisions.

The authors find that bidders' prior information about V is quite diffuse. In their model, ex ante beliefs about V are normally distributed. The standard deviation is 0.56 times the book value of the coin if there is no blemish and 0.59 times the book value if there is a blemish. For instance, the standard deviation of V for a coin with a book value of \$100 with no blemish is \$56. However, the distribution of x has much lower variance than V. For instance, the distribution for x for the coin described above would be normally distributed with a mean equal to V and a standard deviation of \$28. Apparently, after a buyer has spent the time and effort to research a coin, his estimate x is considerably more precise than his prior information about V.

Given their parameter estimates, the authors simulate their structural model to quantify the distortions from asymmetric information. First, they compute the equilibrium bidding strategies for an auction where all of the covariates are set equal to their sample averages (most importantly, the book value is equal to \$47). The bid functions are roughly linear. In this auction, bidders shade their bids to be \$5.50 less than their signals x. Given their uncertainty about V, the buyers bid 10-percent less than their signals to compensate for the winner's curse. Second, they simulate the impact of adding an extra bidder on expectation (since bidders arrive at random). When the expected number of bidders increases, the winner's curse is more severe. Bajari and Hortaçsu find that for an auction with all characteristics set equal to their sample averages, adding an additional bidder reduces equilibrium bids by 3.2 percent as a function of the bidder's signal x. Finally, they study the effect of lowering the variance of V from 0.52 times the book value to 0.1. They find that the bid function shifts upwards by \$2.50.

There are two main limitations to their analysis. First, the results depend on correctly specifying both the game and the parametric assumptions used in the structural model. The common value model that they use is fairly strict. All players are perfectly rational, symmetric, and have normally distributed private information. However, they note that it is not computationally tractable, with current methods, to generalize the model since computing the equilibrium involves high dimensional numerical integration. Second, unlike Pai-Ling Yin (2003) or Jin and Kato (2002), the authors do not have rich ex-post information about the realization of the common value or for bidder uncertainty.

In a related study, Yin (2003) utilizes comparative static predictions of the common-value second-price auction model to test for the presence of common values in eBay auctions for used computers. Based on numerical simulations, Yin establishes that bidding strategies in the common-value second-price auction model respond strongly to changes in the variance of x, a bidder's private signal

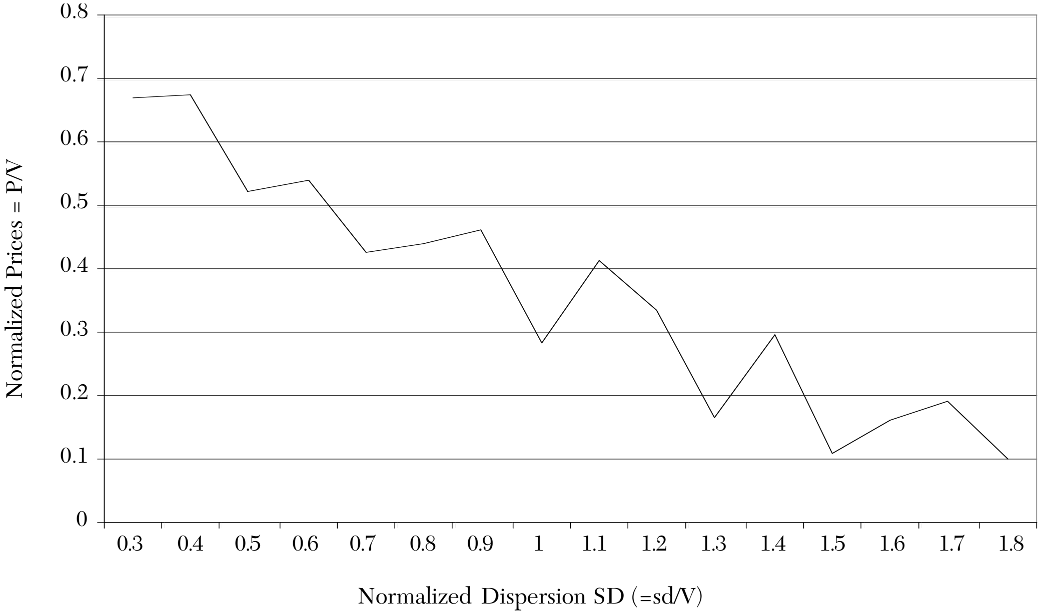


Figure 2. Bidder Uncertainty and Winning Bids

about V. Holding V fixed, if the variance of x increases, the bidder is more likely to be subject to the winner's curse. Conditional on winning, the value of x should be larger holding V fixed. Therefore, bidders should behave more conservatively.

Yin supplements her data set with survey information in order to understand how changing the variance of the signal x influenced bidding. To do this, she downloaded the web pages for 223 completed auctions and asked survey respondents from the internet to reveal their estimates, x, purging information about the bids and the reputation of the seller from the web page so that the survey responses would primarily reflect bidders' ex-ante beliefs about the item for sale and not the seller characteristics. By computing the variance of an average of 46 such responses per auction, she constructed a proxy for the variance of x. The highest variance occurred in the auctions where the seller poorly designed the web page or where the object for sale had inherently ambiguous characteristics.

Yin finds that the winning bid is negatively correlated with the normalized variance of the survey responses. This is illustrated in figure 2. The vertical axis is the winning bid divided by the average survey response. The horizontal axis is the variance of the responses, divided by the average response. For an auction where the normalized variance was 0.4, the expected value of the normalized winning bid was 0.7. As the variance increased to 1.3, the expected value of the normalized winning bid was less than 0.2. Given that the auctions were for computers worth hundreds of dollars, these are fairly large magnitudes.

One interpretation of these results is that bidders act as if they understand the winner's curse. The bidders are reluctant to submit high bids when they are uncertain about the condition of the used computer, as reflected by a high variance in x. On the other hand, if they are more certain about what they are purchasing, they will bid with more confidence. These findings suggest that asymmetric information can generate significant distortions and therefore sellers have a strong incentive to communicate what they are selling by designing a clear web page to reduce bidder uncertainty.

A potential limitation to Yin's analysis is that the variance of x for survey respondents may be an imperfect measure of the variance of x for the real bidders. The survey respondents' reservation values are roughly twice the final sales price on average. Perhaps they are not well informed about used-computer prices. On the other hand, if the winner's curse is a strong possibility, it may be an equilibrium for a bidder to shade his bid to be one half of his estimate x.

Conditional on their caveats, all three papers surveyed in this section suggest that the winner's curse is an important concern in the eBay markets analyzed (baseball cards, collectible coins, used computers). Two of the three papers, Bajari and Hortaçsu (2003) and Yin (2003), find evidence that bidders strategically respond to the presence of a winner's curse. Jin and Kato (2002) also present similar evidence of strategic "bid-shading," but, through their ex-post appraisal of cards sold on eBay, they argue that the amount of bid-shading by bidders in the baseball cards market is not large enough.

As pointed out in the introduction, an important implication of these results, noted by Kazumori and McMillan (2003), is that depressed prices due to the winner's curse may limit the use of online auctions by sellers to items for which informational asymmetries do not play a very large role. Kazumori and McMillan (2003) report that after several years of experimentation with running art auctions on the internet in partnership with eBay, Sotheby's decided to discontinue selling art on the internet as of May 2003. As the authors note, there may have been several confounding factors that led to the failure of Sothebys.com. Fortunately, this still leaves the investigation of the question "which goods can be sold using online auctions" open for further empirical and theoretical analysis.

5. *Reputation Mechanisms*

Perhaps the most important source of information asymmetry on online auctions, aside from the inability to physically inspect goods, is the anonymity of the sellers. For instance, eBay does not require its users to divulge their actual names or addresses; all that is revealed is an eBay ID.[17] There are also very few repeat transactions between buyers and sellers. For instance, Paul Resnick and Richard Zeckhauser (2001), using a large data set from eBay, report that fewer than 20 percent of transactions are between repeated buyer-seller pairs within a five-month period.[18] This obviously limits a buyer's information about the seller's reliability and honesty.

To ensure honest behavior, online auction sites rely on voluntary feedback mechanisms, in which buyers and sellers alike can post reviews of each others' performance. On eBay, a buyer can rate a seller (and vice versa) by giving them a positive (+1), neutral (0), or negative (-1) score, along with a text comment.[19] eBay records and displays all of these comments, including the ID of the person making the comment. eBay also displays some summary statistics of users' feedback. The most prominently displayed summary statistic, which accompanies every mention of a user ID on eBay's web pages, is the number of positives that a particular user has received from other unique users, minus the number of negatives.[20] eBay also computes and reports the number of positives/neutral/negatives that a seller has received in their lifetime, along with the last week, last month, and last six months.

[17] Sellers are also required to list a valid credit-card number.

[18] Resnick and Zeckhauser (2001) had data on transactions conducted on eBay in a five-month period, hence they cannot track transactions preceding this period. Within this time period, however, repeat transactions, if they occurred at all, happened in a very short time period.

[19] Other auction sites, such as Amazon, allow for more nuanced feedback. Amazon, for example, utilizes a scale of 1 to 5.

[20] In March 2003, eBay also began displaying the percentage of positive feedbacks along with the total score.

A prospective buyer on eBay therefore has access to a considerable amount of information about the reputation of a seller. For instance, almost all of the feedback on eBay is positive. Resnick and Zeckhauser (2001) report that only 0.6 percent of feedback comments left on eBay by buyers about sellers was negative or neutral. One interpretation of this result is that most users are completely satisfied with their transaction. Another interpretation, however, is that users are hesitant to leave negative feedback for fear of retaliation. Luis Cabral and Ali Hortaçsu (2003) report that a buyer who leaves a negative comment about a seller has a 40-percent chance of getting a negative back from the seller (whereas a neutral comment has a 10-percent chance of being retaliated against).[21] Another factor limiting the potential usefulness of feedback, reported by Resnick and Zeckhauser, is that feedback provision is an arguably costly activity that is completely voluntary, and that not all buyers (52.1 percent) actually provide reviews about their sellers.

5.1 *Empirical Assessment of Feedback Mechanisms*

Do online reputation mechanisms work? The fact that we observe a large volume of trade on sites like eBay, Yahoo! and Amazon may suggest that the answer to this question is affirmative. However, there have also been a number of attempts to answer this question in a more direct manner, by estimating the market price of reputation in online auctions through hedonic regressions.

Table 1, which is adapted from Resnick et al. (2003), summarizes these empirical studies. The first ten studies on this list used data on completed auctions on eBay to run cross-sectional hedonic regressions of the sale price or sale probabilities of similar objects on sellers' observable feedback characteristics. The (log) number of positive and negative comments is used as a right-hand side variable in almost all of these studies. Some of these studies also attempted to account for nonlinearities in the functional relationship by putting in dummy variables for the existence of negatives, or dummy variables for different ranges of feedback. Some studies also explicitly recognize the truncation problem caused by auctions that did not end in a sale, and estimated a "probability of sale" equation either separately or jointly with the (log) price regression.

As can be seen in table 1, although the signs and statistical significance of the regression coefficients are mostly of the expected kind, the empirical results from these studies are not easily comparable, since some of them are reported in absolute terms and some are reported in percentage terms. We should also note that the absolute number of feedback comments received by sellers follows a highly skewed distribution, reflecting a Gibrat's Law type effect. Given this, however, the starkest differences appear to be between sellers who have no feedback records, and those with a very large number of positive comments. For example, Mikhail Melnik and James Alm (2002) report that the difference between 452 and 1 positive comment is $1.59 for $33 items, implying a price premium of 5 percent. Jeffrey Livingston's (2002) estimates imply a more than 10-percent price premium for sellers with more than 675 positive comments, as opposed to those with no feedback. Similarly, Kirthi Kalyanam and Shelby McIntyre (2001) report that a seller with 3000 total feedbacks and no negatives is estimated to get a 12-percent higher price than a seller with ten total

[21] Resnick and Zeckhauser (2001) also report in a smaller sample that in 18 out of 87 cases (20 percent) where a buyer left negative feedback about a seller, the seller responded with a negative for the buyer. There is also the possibility that some buyers are more critical than others—although eBay allows users to observe the feedback that a user left about others, it does not provide summary statistics of left feedback—hence, making it quite costly for a prospective buyer to gauge the attitude of a particular commentor (other sites that provide user reviews, such as Amazon, allow readers of a comment to rate that comment on the basis of its usefulness).

comments and four negatives. The presence of an up to 10–12 percent price premium between an "established" eBay seller (with hundreds or thousands of feedback comments) and a seller with no track record appears to be the most robust result among these studies, especially in light of the 8.1-percent price premium uncovered by a recent "field experiment" conducted by Resnick et al. (2003) to account for some of the more obvious confounding factors inherent in the hedonic regressions, which we shall discuss now.

The first confounding factor is that the estimate of reputation may be subject to an omitted variable bias. Since there is very little negative feedback, the number of positives is essentially equal to the number of transactions that a seller has completed on eBay. More experienced eBayers are on average more adept at constructing a well-designed web page and responding to buyer questions. The work of Yin (2003) suggests that a well-designed web page has a sizeable effect on final sale prices by reducing buyer uncertainty about the object for sale. As a result, more experienced sellers (as measured by positive feedback) will have higher sales prices for reasons that have nothing to do with reputation.[22] Obviously, these factors could lead to biased estimates that overstate the market value of reputation scores obtained by sellers on eBay.

Sulin Ba and Paul Pavlou (2002), Cabral and Hortaçsu (2003), and Resnick et al. (2003) attempt to reduce this confounding factor by manipulating feedback indicators independently of other characteristics of auction listings. For example, Resnick et al. (2003) conduct a "field experiment" with the help of an established eBay seller (2000 positives, 1 negative), by selling matched pairs of postcards both under the seller's real name and under newly created identities. They report that the established seller received, after correcting for non-sales, 8.1 percent higher prices than his newly formed identity. Ba and Pavlou (2002), on the other hand, asked a sample of eBay bidders to state their willingness to pay for eBay auction listings obtained from the web site, with the twist that seller feedback characteristics were manipulated by the experimenters.[23] Cabral and Hortaçsu (2003) exploited a change in eBay feedback reporting policy: as mentioned before, eBay began displaying the percentage of positives starting in March 2003. Cabral and Hortaçsu (2003) run a hedonic regression where they interact different feedback summary statistics with a dummy variable for the policy change, and show that the negative correlation between prices and the percentage of negatives is larger after the policy change, whereas the correlation between prices and total feedback score, and the seller's age in days, is smaller.

A second limitation of hedonic studies is that there is very little variation in certain independent variables, particularly negative feedback. For instance, in Dan Houser and John Wooders (2003), the maximum number of negative feedbacks in their data set is twelve. Similarly in Melnik and Alm (2002), the maximum number of negatives is thirteen. In the data set analyzed in Bajari and Hortaçsu (2003), we found that only very large sellers with hundreds, if not thousands, of positive feedbacks, had more than a handful of negative feedbacks. Obviously, it is hard to learn about the value of negative feedback when there is not much variation in this variable.

A third limitation is that the objects analyzed in the hedonic studies mentioned above are fairly inexpensive and standardized. Researchers prefer using standardized

[22] Standard models of dynamic industry equilibrium, such as Hugo Hopenhayn (1992) and Richard Ericson and Ariel Pakes (1998), suggest that survival is positively correlated with measures of seller productivity.

[23] There may have been some other confounding factors that Resnick et al. were not able to remove with their experimental design. In particular, some buyers may have been repeat customers of the established seller ID, and some buyers may even have searched (or even had automatic watches) for sales by that seller, and not even looked at the matched listings from the new buyer. We thank Paul Resnick for pointing this out.

TABLE 1
EMPIRICAL STUDIES ON THE VALUE OF REPUTATION ON EBAY
(ADAPTED FROM RESNICK ET AL. 2003)

Source	Items Sold	Mean price	Type of Study	Covariates ("?" indicates dummy variable)
Dewan and Hsu, 2001	Collectible stamps	$37	hedonic regression, compare auction prices on eBay with specialty site (Michael Rogers,Inc)	book value; international transaction?; number of bids; full set?; close on weekend?; buyer's net rating
Eaton, 2002	Electric guitars	$1,621	hedonic regression	guitar type; credit card?; escrow?; pictures?; interaction terms
Houser and Wooders, 2000	Pentium chips	$244	hedonic regression	auction length, credit card, book value, used, processor type
Jin and Kato, 2002	Sports trading cards	$166	hedonic regression	same as (Melnik and Alm, 2002)
Kalyanam and McIntyre, 2001	Palm Pilot PDAs	$238	hedonic regression	product type; picture? number of bids
Livingston, 2002	Golf clubs	$409	hedonic regression	product type; minimum bid; book value; secret reserve?; credit card?; day and time of auction close; length; inexperienced bidder?
Lucking-Reiley et al. 2000	coins	$173	hedonic regression	book value; minimum bid; auction length; end on weekend?; Hidden reserve?
McDonald and Slawson, 2000	collectible Dolls; new	$208	hedonic regression	month
Melnik and Alm, 2002	gold coins in mint condition	$33	hedonic regression	gold price; closing time and day; auction length; credit card acceptance; images; shipping charges
Cabral and Hortacsu, 2003	IBM Thinkpad notebooks, gold coins, mint coin sets, Beanie Babies	$15-$900	hedonic regression	dummy variable for eBay format change date;closing time and day; auction length; credit card acceptance; PayPal; images; whether item is refurbished
Ba and Pavlou, 2002	music CD; modem; Windows Server software CD; digital camcorder	$15- $1200	lab experiment in the field: subjects responded with trust level and willingness to pay for auction listings with different feedback profiles spliced in.	showed identical listings with different feedback profiles
Resnick et al. 2003	vintage postcards	$13	field experiment	showed matched information for matched items, in different display format
Cabral and Hortacsu, 2003	IBM Thinkpad notebooks, gold coins, mint coin sets, Beanie Babies	$15-$900	panel regression using backward-looking feedback profiles of a cross-section of seller	control for seller fixed effects, age in days, reviewer profile

TABLE 1 *(cont.)*

Modeling Specification	Results regarding market value of reputation
OLS for sold items only; ln(price) vs. ln(positive-negative)	20 additional seller rating points translate into a 5 cent increase in auction price on eBay. Average bids higher on specialty site, but seller revenues on specialty site (after 15% commission) are same with revenues on eBay.
reduced form, logit on probability of sale, OLS on items sold: positives (number); negatives (dummy or number)	No robust statistically significant relation between negative feedback and probability of sale and price of sold items
model of bidder distributions based on private values motivates reduced-form GLS (on sold items only), with expectation of more bidders for longer auctions; ln(high-bid) vs. ln(pos), ln(non-positive)	10% increase in positive feedback increases price 0.17%; 10% increase in negative feedback reduces it by 0.24%. Increasing positive comments from 0 to 15 increase price by 5%, or $12.
probit predicts probability of sale; OLS for sold items, ln(price/book) vs. ln(net score), has negatives?	Positive feedback increases probability of sale; negative decreases probability of sale unless card is professionally grade; no significant effects on price
OLS for sold items only; price against positives, negatives, interaction terms	Seller with 3000 total feedback and 0 negatives gets 12% higher price than a seller with 10 total feedback and 4 negatives
probit predicts probability of sale; simultaneous ML estimation of price if observed, probability of sale; reputation specifed by dummies for quartiles of positive feedback, fraction of negative	Sellers with 1 to 25 positive comments receive $21 more than sellers with no reports. Sellers with more than 675 positive comments receives $46 more. The first 11 good reports increase probability of receiving a bid 4%, subsequent reports do not appear to have a statistically significant effect on sale probability.
reduced form, censored normal regression; ln(high-bid) vs. ln(pos), ln(neg)	No statistically significant effect from positive feedback; 1% increase in negative feedback reduces price by 0.11%.
Simultaneous regression for sold items only: price against bids, reputation; bids against minimum bid, secret reserve, reputation. Various specifications of reputation	High reputation seller (90th percentile of eBay rating) gets 5% higher price than low reputation (10th percentile) and gets more bids
reduced form, censored normal regression; ln(high-bid) vs. ln(pos), ln(neg), ln(neutral)	Decline of positive ratings from 452 to 1 decreases price by $1.59 for $32 items; halving negative feedback from 0.96 comments to 0.48 comments increases price by 28 cents.
OLS; ln(highbid) vs. % of negatives, total number of feedbacks, age of seller in days	Effect of % negatives increases after eBay begins to report percentages in March 2003 (8% price premium if % negatives declines 1 point). Effect of total no. of feedbacks and age of seller declines after format change. Effect most visible for Thinkpads.
OLS, ANOVA of trust, price premium, against ln(positive), ln(negative)	Buyers willing to pay 0.36% more if feedback profile has 1% more positives, -0.63% less with 1% more negatives (Table 8). Effect is larger for higher priced items.
censored normal: ln(ratio of prices) dep variable with no independent variables	Seller with 2000 positive comments and 1 negative fetched 8% higher prices for matched items sold by newly created seller identities with 10 positives on average. Sale probability of large seller 7% higher than new sellers. One or two negatives for a relative newcomer had no statistically detectable effect over other newcomers.
look at the impact of first vs. subsequent negatives on sales growth, where sales levels are proxied by the number of feedbacks received; look at the timing between negatives	In 4 week window after first negative, sales growth rate is 30% less than in 4 week window before negative; second negatives arrive faster than first negatives

objects because it is fairly easy to collect book values, which are an important independent variable in hedonic regressions, for such items. Fairly inexpensive items are typically used because they are representative of the objects bought and sold in online markets.

It is arguable, however, that the role of reputation is most important when a buyer is considering the purchase of a very expensive item of potentially dubious quality. When a buyer is purchasing a new, branded, and standardized object (e.g., a new Palm Pilot) there is probably little uncertainty about the item up for sale. When the item is expensive, used, and has uncertain quality, such as a hard-to-appraise antique, reputation might play a more important role. A buyer in such an auction might be reluctant to bid thousands of dollars when the seller has only limited feedback. Such items, however, have typically not been included in previous studies since it is difficult to construct appropriate controls for the value of such an item. In particular, book values for such items are probably not very meaningful.

A final limitation, which applies equally to both the hedonic regressions and the field-experiment studies, is that it is difficult to interpret the "implicit prices" as buyer valuations or some other primitive economic object. In the applied econometric literature on hedonics, such as Sherwin Rosen (1974) and Dennis Epple (1987), there is a fairly simple mapping from "implicit prices" to buyer preferences. The implicit price can typically be interpreted as the market price for a characteristic. Hence the implicit price is equal to the marginal rate of substitution between this characteristic and a composite commodity. This straightforward mapping breaks down when there is asymmetric information.

The winning bid in an auction is a complicated function of the underlying private information of all of the bidders. Only fairly stylized models of auctions would let the economist directly interpret the coefficient on feedback as a marginal rate of substitution between reputation and a composite commodity. In the framework of L. Rezende (2003), if the economist makes the following assumptions, then the standard hedonic interpretation of implicit prices is valid:

1. There are private values and there is no asymmetric information among the bidders about the marginal value of the observed product characteristics.
2. There are no minimum bids or reserve prices.
3. All bidders are ex ante symmetric.
4. There are no product characteristics observed by the bidders but not the economist.
5. Entry is exogenous and a dummy variable for the number of bidders is included in the regression.

Clearly, these may be strong assumptions in many applications. In particular, a large fraction of online auctions uses minimum bids or secret reserve prices. Also, it could be argued that uncertainty about quality naturally induces a common-value component into the auction.

Many of the papers in the literature do not articulate a primitive set of assumptions under which the regression coefficients can be interpreted as a measure of buyers' willingness to pay for characteristics (such as reputation) or some other primitive economic parameter. While this limits the generality of the conclusions, it is nonetheless interesting to know the conditional mean of the sale price as a function of characteristics.

5.2 *Other Tests of the Theory*

In addition to measuring the market price of a reputation, several other empirical observations have been made about feedback mechanisms. For example, Ba and Pavlou (2002) report that the impact of variation in feedback statistics is larger when the value of the object being sold is higher. This is consistent with economic intuition—the value of a reputation is more important for "big ticket" items. Jin and Kato (2002) and Louis Ederington and Michael Dewally (2003) find that for collectible objects for which professional grading is an option, sale prices of ungraded objects respond more to eBay's feedback statistics than graded objects. This is consistent with our conjecture above—reputation is more important the less certain the buyer is about the quality of the item that is for sale.

Cabral and Hortaçsu (2003) investigate whether sellers respond to the feedback mechanism. They use the feedback profiles of a cross-section of active sellers to construct a backward-looking panel data set that tracks the comments received by the sellers. They find that, on average, the number of positive comments received by a seller until their first negative is much larger than the number of positive comments received between their first and second negatives. They investigate a number of alternative hypotheses for this phenomenon; in particular the possibility that buyers may be reluctant (possibly due to altruistic reasons) to be the first one to "tarnish" a seller's reputation. They find that buyers who place the first negative are not, on average, more likely to give negative comments than the buyers who gave the subsequent negatives. Moreover, they do not find an observable difference between the textual content of first vs. subsequent comments.

5.3 *Do Reputation Mechanisms Work*?

Given the various results in the literature, it is natural to attempt to reach a judgment as to whether reputation mechanisms achieve their purpose of reducing trading frictions on the internet. The robust growth in the number of users and transactions on eBay could be regarded as a testament to the fact that fraud is not perceived as a huge deterrent in these markets. However, a number of authors express skepticism about the effectiveness of the feedback systems used in online auctions. For example, the study by Jin and Kato (2002), which we discussed in section 4, takes the stance that the observed patterns of trade cannot be explained by rational buyers. The conclusion they reach in their study is that the prices ungraded cards were fetching on eBay were higher than could be rationalized by the frequency of fraudulent claims in their graded sample. They also found that although reputable sellers were less likely to make fraudulent claims and were also less likely to default or deliver counterfeits, the premium that buyers pay for reputation (after correcting for sales probability) is much lower than the premium that buyers pay for self claims. Hence they conclude that "In the current online market, at least some buyers drastically underestimate the risk of trading online" and that "… some buyers have difficulty interpreting the signals from seller reputation." The study by Resnick et al. (2003) also concludes with the statement that: "Nevertheless, it is hardly obvious that this reputation system would work sufficiently well to induce reliable seller behavior."

We believe that the jury is still out on the effectiveness of the reputation systems implemented by eBay and other online auction sites. There is still plenty of work to be done to understand how market participants utilize the information contained in the feedback forum system, and whether some of the seemingly obvious deficiencies of these systems, such as the free-riding problem inherent in the harvesting of user reviews and the presence of seller retaliation, are large enough to hamper the effectiveness of these systems. As in the analysis of the "late-bidding" phenomenon, perhaps controlled laboratory experiments can help shed more light into how different components of this complex problem work in isolation from each other.[24]

[24] A pioneering attempt in this direction is a laboratory experiment by Gary Bolton, Elena Katok, and Axel Ockenfels (2003), which shows that while reputation mechanisms induce a substantial improvement in transactional efficiency, they also exhibit a kind of public goods problem in that the reporting of honest or dishonest behavior have external benefits to the community that can not be internalized by the individual making the report.

6. *Auction Design Insights from Internet Auctions*

Perhaps the most central question that auction theorists try to answer is "What kind of an auction should I use to sell my goods?" Since Vickrey's (1961) seminal paper, a large body of theoretical literature has investigated how various informational and strategic factors in the auction environment affect the decision of how one should design auctions.[25] Economic theorists studying auctions have also been influential in the design of important, high-profile auctions such as wireless spectrum auctions, and the design of deregulated energy markets across the world.

The dramatic development of our theoretical understanding of auction theory and the increasing scope for real-world applications also drive a natural need for empirical assessment of how these theories perform in the real world. To this date, most empirical research on auctions has been conducted in laboratory experiments. Laboratory experiments are well-suited for this purpose, since the empirical researcher has control over the design of auction rules and the flow of information to participants.[26] However, most laboratory experiments employ college students as their subjects, who are typically not experienced bidders, and are given relatively modest incentives (by the yardstick of corporate wages). Hence, empirical researchers hailing from nonexperimental branches of economics have frequently questioned the extent to which laboratory experiments can replicate "real-world" incentives.

There are important difficulties, however, with the use of data from nonexperimental, real-world auctions for empirical testing of theories. First, in most field settings of interest, it is very costly to conduct controlled, randomized trials; hence, statistical inferences based on nonexperimental data are typically subject to much stronger assumptions than inferences from experimental data. Second, detailed transactions data from real markets is typically not easy to get, since such data is sensitive and confidential information in many industries.

Internet auctions provide a very interesting and promising middle ground between controlled laboratory experiments conducted with student subject pools and large-scale field applications such as wireless spectrum auctions or energy auctions. First, data on bids are readily available from online auction sites, lowering this important "barrier-to-entry" for many empirical researchers. Second, as discussed in section 3, there are differences across the auction rules utilized across different auction sites or even within an auction site, and these differences can be exploited to empirically assess whether one mechanism works better than another. Third, empirical researchers can actually conduct their own auctions on these sites, which allows them to run randomized "field experiments" with experienced, real-world subject pools.

We now survey several examples of how the study of internet auctions has provided novel and potentially useful insights regarding economic theories of auction design.

6.1 *Field Experiments on the Internet*

In a set of "field experiments," David Lucking-Reiley (1999a) tests two basic hypotheses derived from auction theory: 1) the strategic equivalence[27] between the open descending price (Dutch) and sealed-bid first-price auction, and 2) the strategic

[25] See the survey articles by R. Preston McAfee, and John McMillan (1987), Paul Klemperer (1999), and the recent textbook by Vijay Krishna (2002).

[26] For a comprehensive survey of experimental work on auctions, see Kagel and Roth (1995, ch. 7).

[27] According to Krishna (2002), page 4, footnote 2: "Two games are strategically equivalent if they have the same normal form except for duplicate strategies. Roughly this means that for each strategy in one game, a player has a strategy in the other game, which results in the same outcomes." In this context, strategic equivalence means that fixing the valuation constant, bids should be the same across the two auctions.

equivalence between second-price and English auctions.[28] As discussed in Paul Milgrom and Robert Weber (1982), the strategic equivalence between Dutch and sealed-bid first-price auctions follows quite generally, since the only piece of information available to bidders in a Dutch auction that is not available to bidders in a sealed-bid first-price auction is whether a bidder has claimed the object. But this information cannot be incorporated into bidding strategies, since its revelation causes the auction to end.

On the other hand, the strategic equivalence between second-price and English auctions only applies in a private-values environment, where bidders would not modify their personal willingness to pay for the object even if they knew how much other bidders were willing to pay. It can be shown that with private values, bidding one's value, or staying in the auction until the price reaches one's valuation is a (weakly) dominant strategy in both the second-price auction and the English auction. In an interdependent-values or common-value environment, however, seeing another bidder's willingness to pay may affect the inference one makes regarding the value of the object, and hence changes their willingness to pay. As shown by Milgrom and Weber (1982), bidding strategies may be very different in an English auction in which drop-out points of rival bidders are revealed, as opposed to sealed-bid second-price auctions, where bidders do not observe each others' actions, and hence cannot update how much they are willing-to-pay for the object during the course of the auction.

Lucking-Reiley's experiment used the above auction formats to sell trading cards for the role-playing game, Magic: The Gathering, on an internet newsgroup that was organized as an online marketplace for enthusiasts in "pre-eBay" days. Lucking-Reiley invited participants to his auctions using e-mail invitations and postings on the newsgroup. To minimize differences across participants' distribution of values for the auctioned cards, Lucking-Reiley used a "matched-pair" design. For example, in the comparison of first-price and Dutch auctions, he first auctioned a set of cards using the first-price auction; a few days after his first set of auctions ended, he sold an identical set of cards using a Dutch auction. To account for temporal differences in bidders' demand for these cards, Lucking-Reiley repeated the paired experiment about four months later, but this time selling the first set using Dutch auctions, and the second set using first-price auctions.

Lucking-Reiley found that Dutch auctions yielded 30-percent higher average revenue than the first-price auctions, and rejected the strategic equivalence of the two auction formats. On the other hand, in the second-price vs. English auction experiment, he found that the auction formats yielded statistically similar revenues. However, he found less convincing evidence for the hypothesis that the two auctions were strategically equivalent. In particular, he found that in 81 out of 231 cases where the same bidder placed a bid for the same card on both an English auction and a second-price auction, the bidder's highest English-auction bid exceeded their bid on the second-price auction.[29]

[28] Briefly, the auction formats are the following: in the sealed-bid first-price auction, the highest bidder wins the auction and pays the price bid. In the sealed-bid second-price auction, the highest bidder wins, but pays the second-highest bid. In the Dutch auction, price decreases continuously from a high starting value, and the first bidder to claim the object wins the auction and pays the price at the instant she called in. In the English auction considered here, price rises continuously, and all bidders indicate (by pressing a button, for example) whether they are still in the auction or not. The auction ends when the second-to-last bidder drops out, and the winner pays the price at which this final drop-out occurs. Bidders cannot rejoin the auction once they have dropped out.

[29] This finding does have an alternative explanation in that bidders have decreasing marginal valuations for the cards.

We should note that previous studies using laboratory experiments, by Vicki Coppinger, Vernon Smith, and Jon Titus (1980) and James Cox, Bruce Roberson, andVernon Smith (1982) also rejected the strategic equivalence of first-price auctions with descending auctions. However, these experiments reported higher prices in first-price auctions than Dutch auctions, with Dutch auctions yielding 5-percent lower revenues on average. Similarly, John Kagel, Ronald Harstad, and Dan Levin (1987) report the failure of strategic equivalence of the second-price and English auctions in the laboratory setting. In particular, they report a tendency for subjects to bid above their valuations in the second-price auction, whereas they rapidly converge to bidding their values in the English auction, yielding 11 percent higher revenue for the second-price auction.

What explains the differences across Lucking-Reiley's results and results from laboratory experiments? First of all, as Lucking-Reiley notes, his field experiment cannot control for the entry decisions of the bidders; he reports that Dutch auctions attracted almost double the number of bidders as his first-price auctions, and it is not hard to see that an increase in the number of bidders would increase revenues. The causes of the higher participation in the Dutch auction remains a mystery: Lucking-Reiley argues that this is not solely due to the novelty of the Dutch auction mechanism, since market participants had been exposed to Dutch auctions before. One wonders, however, whether a "taste for novelty" effect may persevere over longer periods of time.[30]

[30] Lucking-Reiley also discusses whether the speed at which prices decline in Dutch auctions may have led to a difference between his results and laboratory results; in his field experiment, prices declined much slower than in the laboratory. Interestingly, Elena Katok and Anthony Kwasnica (2000) find, in a laboratory setting, that slower price declines in Dutch auctions led to increased revenues as compared to sealed-bid auctions, suggesting that bidder impatience may have played a role in the field experiment setting.

Second, Lucking-Reiley's experiment cannot control for the informational structure of the auction. In the laboratory, the researcher can choose whether to run a common/interdependent value or a private-value auction; however, Lucking-Reiley cannot predetermine whether bidders will regard his trading cards as private-value or common-value objects. This may affect the interpretation of his second-price vs. ascending auction results: in a common-value environment, the second-price auction is predicted to yield lower average revenues. This factor, compounded with the experimentally reported bias of the bidders to overbid, may result in the observed revenue equivalence result.

On the other hand, one may think that the online marketplace utilized by Lucking-Reiley is populated by veterans of previous auctions, who are experienced enough not to overbid in a second-price auction—hence the theoretical prediction of revenue equivalence is more likely to be borne out in the field than in the laboratory. Lucking-Reiley briefly mentions this possibility; though more direct evidence comes from elsewhere. In a recent paper, Rod Garratt, Mark Walker, and John Wooders (2002) invited experienced bidders on eBay to take part in second-price auction experiments conducted in a laboratory setup. In contrast to previous experimental findings, Garratt, Walker, and Wooders found that bidders experienced on eBay do not overbid in second-price private-value auctions, and, very often, give the correct reasoning to their action. Hence, field-experiments conducted on online auction sites may indeed provide a more qualified subject pool for auction experiments.

Another argument for the use of field experiment methodology, as pointed out by Lucking-Reiley (1999b), is that in practical settings where a seller is trying to assess the proper auction mechanism to use, controls for endogenous entry decisions and on the informational environment will typically not be present. For example, the fact that a

Dutch auction may lead to higher bidder participation may be an outcome variable of interest to a seller considering switching to this auction format; especially since it leads to higher revenues. Hence, Lucking-Reiley argues that for practical or policy applications, results of field experiments may provide more insights regarding the outcome of a possible policy change.

The field experiment methodology also has advantages over nonexperimental analyses of outcomes across different auction formats. As Lucking-Reiley notes, a nonexperimental analysis of whether a first-price or a second-price auction yields higher revenues may have to worry about why some auctions were conducted using a first-price auction, and others using a second-price auction.[31] On the other hand, we should note that the field experimentation methodology, as used by Lucking-Reiley, can only shed light onto partial-equilibrium responses to changes in mechanism design. For example, his finding that Dutch auctions yield 30-percent higher revenues than first-price auctions may not apply if every seller on an auction site decides to use a Dutch auction as opposed to a first-price auction.[32]

Whatever its pros and cons, Lucking-Reiley's paper is a good example of how online auction sites can be used as a laboratory for creative field experiments. Last, but not least, we should point out that a very important advantage of this "field laboratory" is that it was relatively inexpensive to use: Lucking-Reiley's experiment had an initial cost of $2,000 to buy about 400 trading cards, which he claims to have recouped with a profit (in addition to a published thesis chapter) after selling them. Moreover, at the cost of some lack of customizability, online auction sites make it easy for the researcher to set up and track experiments; instead of requiring them to spend a significant amount of programming time to write software for their own experiments.

6.2 *Should Reserve Prices Be Kept Secret*?

Auction design is not only about choosing between formats such as first-price, second-price, English or Dutch. As first shown by Roger Myerson (1981), a seller may significantly increase their revenues by optimally setting a publicly observable reserve price, or, equivalently, a minimum bid.

A look at sellers' practices of setting reserve prices on eBay reveals an interesting regularity: as noted by Bajari and Hortaçsu (2003), many sellers on eBay, especially those selling higher-value items, choose to keep their reserve prices secret, as opposed to publicly announcing it. This immediately brings up the question: "When, if ever, should one use a secret reserve price, as opposed to a publicly observable minimum bid?"

Auction theory has been relatively silent regarding this question, with two notable exceptions. Li and Tan (2000) show that with risk-aversion, secret reserve prices may increase the auctioneer's revenue in an independent private value first-price auction, but in second-price and English auctions, regardless of the bidders' risk preferences, the auctioneer should be indifferent between setting a secret vs. observable reserve price. Daniel Vincent (1995) provides an example in which setting a secret reserve price in an interdependent value second-price auction can increase the auctioneer's revenues. Vincent's basic intuition is that the minimum bid censors some bidders, and the inference drawn by participants in the auction from this censored distribution may lead to lower bids than inference from the uncensored distribution.

Given the above theoretical results, especially that of Vincent (1995), Bajari and Hortaçsu (2003) estimate bidders' common-value and private signal distributions in a symmetric common-value second-price

[31] Lucking-Reiley quotes Robert Hansen's (1986) finding of systematic differences in timber lots sold using sealed-bid vs. ascending auction by the U.S. Forest Service.

[32] Lucking-Reiley notes that the marketplace was active enough that his 80 auctions would not have a "market-wide" impact.

auction model of eBay coin auctions, and use these parameter values to numerically compute optimal minimum bid and secret reserve price levels to compare the revenues expected from these two pricing policies. They find that, at its optimal level, a secret reserve price can yield the seller 1 percent higher expected revenue.

Rama Katkar and David Lucking-Reiley (2000) question the validity of the behavioral assumptions used in Bajari and Hortaçsu's (2003) structural econometric model, and attempt to answer the same question using a field experiment. In their experiment, the authors bought and sold fifty matched pairs of Pokemon trading cards on eBay, auctioning one card in the pair using a publicly announced minimum bid, and the other using a secret reserve price that was set equal to the minimum bid. They found that the secret reserve price auctions yielded 60 cents less revenue on average (average card value was approximately \$7). They also reported that secret reserve price auctions were less likely to end in a sale.

Although Katkar and Lucking-Reiley (2000) have a valid point in questioning the structural econometric approach of Bajari and Hortaçsu (2003), especially with regard to its imposition of fully rational behavior by the bidders, the field-experiment approach they utilize is also subject to important caveats. For example, an important feature of Katkar and Lucking-Reiley's experiment is that the minimum bids and the secret reserves were assigned arbitrarily, and were kept constant across treatments. Under the assumption of seller rationality, a more appropriate comparison should be between the *ex-ante revenue-maximizing* values of the minimum bid and the secret reserve price, which might not necessarily be the same. Unfortunately, deriving *ex-ante revenue-maximizing* values of the choice variables above is actually not a very straightforward exercise, since, as first derived by Myerson (1981), a calculation of the revenue-maximizing minimum bid depends on the distribution of bidders' valuations—which must be estimated from bidding data.

The previous discussion underlines some of the subtleties underlying the analysis and interpretation of experimental or nonexperimental data from online auction sites for the purpose of evaluating mechanism design alternatives. The treatment effects estimated using a randomized field experiment, such as Katkar and Lucking-Reiley (2000), may not always have a clear interpretation within the context of a theoretical model. Structural econometric models, as utilized in Bajari and Hortaçsu (2003), have the advantage that their estimates can be readily interpreted within the context of a theoretical model, but their results may not always be robust to specification error, or problems associated with the nonexperimental nature of the data. The user of either approach should be very clear about the shortcomings of the respective methods; and, if possible, use the two methodologies in a complementary manner.

Coming back to the question of whether empirical studies have taught us anything about the use of reserve prices, we should note that both of the papers surveyed here are unable to provide a very satisfactory answer to the question: "If one reserve price mechanism revenue-dominates the other, why do sellers persist in using the dominated mechanism?" Katkar and Lucking-Reiley quote an additional "benefit" of the secret reserve price strategy that their experiment does not account for—by setting a very high secret reserve, a seller may first screen out the bidders with the highest valuations for the object, and later contact them away from eBay to run a private transaction for which he does not have to pay commission to eBay. On the flip side, Bajari and Hortaçsu (2003) mention an additional "cost" of using a secret reserve price auction: some buyers, especially new participants who do not quite understand the rules of eBay, may get angry upon not winning an auction due to a secret reserve and place a negative comment on the seller's record.[33] However, neither paper provides a satisfactory reconciliation of these various costs and benefits to explain the patterns of usage of different reserve-price strategies on eBay. We believe this may be an interesting avenue for future research.

6.3 *The Prevalence of Ascending Auctions*

A casual observer of online auction sites will immediately observe the following pattern: all three major online auction sites (eBay, Yahoo!, Amazon) use the proxy-bidding format (albeit with differing ending rules, as discussed in section 3). In a much more comprehensive survey, Lucking-Reiley (2000b) found that 121 of the 142 internet auction sites he surveyed in 1998 used an ascending auction format. Seven sites used a first-price sealed-bid auction and eight used a second-price sealed-bid auction.[34]

What is so special about the proxy-bidding mechanism, or open-ascending auction formats in general? A similar question was posed in an earlier survey article by McAfee and McMillan (1987) regarding the prevalence of ascending auction formats in the "brick-and-mortar" era preceding the internet. McAfee and McMillan (1987) suggest an explanation based on the theoretical results of Milgrom and Weber (1982). As discussed in section 4, in many of the auctions conducted on these sites, a common value or interdependent values element may be present. As shown by Milgrom and Weber (1982), the open-ascending English auction yields higher expected revenues than its sealed-bid counterparts—intuitively due to the fact that a lot of information about other bidders' valuations is revealed during the course of an English auction, and hence bidders are not as compelled to shade their bids to combat the winner's curse. This does not automatically mean, however, that ex ante, bidders expect to gain less surplus from participating in an English auction as opposed to a sealed-bid auction. The English auction can yield more revenue to the seller because more information is revealed during this auction, as opposed to in a sealed-bid auction. Left to their devices, bidders in a sealed-bid auction might have chosen to buy some of this information. Hence, from the perspective of sellers, buyers, and the site operator alike, the use of an open-ascending auction format such as the English auction yields benefits to all: the sellers gains higher revenues, the buyers avoid the winner's curse, and the site operator gains higher commissions.[35]

Several alternative explanations for the prevalence of ascending auctions have been suggested in the literature. The Milgrom and Weber (1982) explanation applies to isolated, single-unit auctions. However, as Lucking-Reiley (2000b) points out, on sites like eBay, there are many sellers trying to sell the same type of good simultaneously. Hence, one intuition suggested by Lucking-Reiley is that with open ascending auctions, bidders may have an easier time deciding which auction to bid on. Peters and Severinov (2001) make this intuition more rigorous. In an independent private-value setting where there are many simultaneous English auctions of the same good, they show that the following is a perfect Bayesian equilibrium strategy for a

[33] We should note that this is no longer possible on eBay, since feedback is restricted to being transaction specific.

[34] We should note that although first-price sealed bid auctions are quite common in offline contexts such as procurement, second-price auctions were quite rare. For a historical account of the use of second-price or Vickrey auctions, see Lucking-Reiley (2000a).

[35] We should note, however, that the use of a hard-deadline ending rule can nullify this benefit of using an ascending auction, since rampant sniping leads to much less information revelation during the auction.

[36] We should note that in Peters and Severinov's model, all auctions end at the same time.

bidder: place a bid in the auction with the lowest current price and raise your bid as slowly as possible, until you reach your valuation.[36] The resulting equilibrium will then lead to all bidders paying a uniform market-clearing price, which is equal to the valuation of the highest losing bidder. Thus, there is no need for an active market-maker to solicit bids and offers from buyers and sellers and match them using a rule such as Walrasian market-clearing—the decentralized equilibrium leads to an ex-post efficient allocation (one in which no buyer regrets the price at which they bought). Observe that although Peters and Severinov's prescribed equilibrium strategy requires bidders to be very attentive (or utilize automated bidding software, versions of which are available on the internet), the decision problem of a bidder facing multiple simultaneous sealed-bid auctions is considerably more complicated, leading, in many cases, to randomized entry decisions.[37]

However, there are also several reasons why sealed-bid auctions may be preferred to open-ascending auctions. As shown by Charles Holt (1980) and Matthews (1995), if bidders have decreasing absolute risk aversion (DARA) preferences, equilibrium bids, and hence the seller's expected revenue in the sealed-bid first-price auction, are higher than in the English auction. Moreover, as shown by Marc Robinson (1985), and McAfee and McMillan (1992), collusion may be more difficult to sustain in sealed-bid first-price auctions as opposed to English auctions.[38]

Motivated by this empirical pattern, Radosveta Ivanova-Stenzel and Tim Salmon (2003) ran an experiment in which they allowed bidders to choose, for an entry fee, between a sealed-bid first-price auction and an English auction.[39] The authors report that when entry prices for the two auction formats are the same, the subjects overwhelmingly preferred the English auction. By varying the entry prices across the formats, the authors attempted to measure bidders' willingness to pay for the English auction. The observed willingness to pay for the English auction, however, was much higher than the profit differential implied by the risk-aversion explanation, which led the authors to conclude that there is a yet-unexplained "demand" component that drives bidders' revealed preference for the English auction.

We believe that Ivanova-Stenzel and Salmon's (2003) study is an important first step towards understanding the economic forces shaping the demand for different types of trading mechanisms. Auction theory is almost exclusively couched in a "partial-equilibrium" framework, where competition between different trading mechanisms is seldom studied.[40] Studying demand and supply patterns on the internet may prove quite fruitful in future research in this area, since data on prices and quantities is relatively easy to obtain, and wide variation across markets/types of goods can be observed.

6.4 *Endogenous Entry Decisions of Bidders*

Another theoretical question that has been put under empirical scrutiny by both field experimentation and structural econometric modeling is the endogenous entry decisions of bidders. As noted by Levin and

[37] This is not to say that there aren't mixed strategy equilibria in the game constructed by Peters and Severinov; however, in many plausible versions of the simultaneous sealed-bid auction game, there are no symmetric pure strategy equilibria.

[38] This may explain why sealed-bid auctions are very prevalent in procurement contexts, where there is repeated interaction within a small group of bidding firms. On internet auction sites, free-entry, geographic dispersion, and anonymity of bidders may make collusion much harder to sustain.

[39] The experiments were independent private value auctions, with the distribution of valuations kept constant across auction formats. The subjects did not observe their valuations prior to choosing the auction format to participate in.

[40] Two notable exceptions are McAfee (1993) and Peters and Severinov (1997).

Smith (1994), most theoretical revenue comparisons between auction formats take the number of participants in the auction as given. Even on eBay, however, bidders may incur costs to bid in an auction, albeit these may be as the time spent searching for the right auction, or the time spent watching the bidding come to a close (though some may also derive enjoyment from the process). Hence, a more realistic model of bidding in an auction should endogenize the number of participants, where the bidders weigh the expected benefit from winning the auction against the cost of participating. This, in turn, means that auction mechanisms that offer different expected surpluses to the bidders will attract different numbers of bidders; and hence the revenues generated by the alternative auction designs cannot be compared under the assumption that the same number of bidders participate in both. In fact, Levin and Smith (1994) argue that this may lead to a more general revenue equivalence principle, since expected payments to bidders should be equalized across two auction mechanisms when the choice is present, and the expected revenues of the sellers should also equalize.

The analysis of online auctions suggests that entry costs, and hence the endogenous entry decisions of bidders, are indeed quite important, and should be taken into account when modeling the performance of alternative trading rules in such environments. Lucking-Reiley (1999b) once again uses the field-experiment method to assess the entry costs of bidders in online auctions. He notes that when he auctioned several trading cards simultaneously with zero minimum bids on each, very few bidders placed bids on every item, and argues that this is consistent with the presence of bidding costs. He also finds, not very surprisingly, that higher minimum bids on otherwise comparable auctions resulted in fewer participants (a finding also corroborated by correlations reported by McAfee, Quan, and Vincent 2002; Bajari and Hortaçsu 2003; Lucking-Reiley et al. 2000). [41]

7. *Conclusion*

Internet auctions are the subject of a rapidly growing body of research. Interest in these markets stems from two factors. First, internet auctions are an inexpensive source for high-quality data. In empirical economics, our data is often a very incomplete representation of the markets that we study. Typically, the researcher cannot measure important product characteristics that determine consumers' choices. Also, we cannot always observe all of the relevant actions of buyers and sellers. In online auctions, the economist is able to observe almost all of the product information that is available to the bidders. Also, the actions of buyers and sellers are recorded in minute detail. The exact time and amount of the proxy bids and the sellers' reserve price policies can easily be downloaded. Second, online auctions are a natural testing ground for auction theory. A substantial body of economic theory studies how to optimally design an auction. In online auctions, we can see how the mechanisms examined in theory perform in the field.

Given the easy access to high-quality data and constant evolution of these trading mechanisms, we predict that the study of internet auction markets will continue to generate interest among many researchers. In particular, we believe that the study of these markets provides a very exciting interface for experimental, theoretical, and

[41] A quantification of the magnitude of these entry costs, however, requires the imposition of a model of entry to calculate the trade-off between the expected benefit from participation and the cost of bidding. Bajari and Hortaçsu (2003) use their structural model to estimate the implied cost of bidding on eBay coin auctions to be around $3; a significant cost, given that the average object in their sample was worth $47. It is interesting to note that several internet services like eSnipe and AuctionWatch, along with eBay itself, have invested in developing technologies to make it easier for bidders to search listed auctions, to monitor progress in simultaneous auctions by creating watchlists, and to place "snipe" bids in the auctions they are participating in.

econometric researchers to bring their methodological toolkits together. Some important research areas remain to be explored. For example, we believe that current research on the design of reputation mechanisms and rating systems to help resolve information asymmetries in online trading environments is still in its infancy. Such a research program will undoubtedly open new questions regarding how people process and transmit information and how incentives affect this; we believe there are many interesting insights to be gained by observing the experimentation of internet auction sites with different "reputation" mechanisms. The design of reliable feedback and quality-enforcement systems is of central importance to internet auction businesses, and insights from this research program can have a lasting influence on the way their web sites are designed.[42] We also observe many businesses selling their goods through eBay and other auction sites, often using fixed-price mechanisms (such as the "Buy-It-Now" feature on eBay) rather than auctions. In our opinion, the economic trade-offs between fixed-prices versus auctions are still largely unexplored, and the analysis of this question will benefit very much from careful observation of what happens on the internet. We also think that important theoretical and econometric challenges exist in the analysis of markets with multiple simultaneous auctions—which is a more accurate characterization of market clearing on large internet auction sites like eBay. Pioneering attempts like the work of Peters and Severinov (2001) exist, but we believe that much more needs to be done in this area.

[42] In fact, as discussed in section 5.1 and in Cabral and Hortaçsu (2003), eBay has already changed the way it calculates and reports feedback statistics. The most recent site change, in response to user comments and internal development efforts, was implemented in late 2003. For the details of this change, see http://pages.ebay.com/services/forum/newfb.html.

References

Ariely, Dan; Axel Ockenfels and Alvin Roth. 2003. "An Experimental Analysis of Ending Rules in Internet Auctions." work. paper, Harvard Bus. School.

Athey, Susan and Philip Haile. 2002. "Identification in Standard Auction Models," *Econometrica* 70:6, pp. 2107–40.

Ba, Sulin and Paul Pavlou. 2002. "Evidence of the Effect of Trust Building Technology in Electronic Markets: Price Premiums and Buyer Behavior," *MIS Quart.* 26:3, pp. 243–68.

Bajari, Patrick and Ali Hortaçsu. 2003. "The Winner's Curse, Reserve Prices and Endogenous Entry: Empirical Insights from eBay Auctions", *Rand J. Econ.* 3:2, pp. 329–55.

Baron, David P. 2002. "Private Ordering on the Internet: The EBay Community of Traders," *Bus. Politics (online)*, 4:3.

Bolton, Gary E.; Elena Katok and Axel Ockenfels. 2003. "How Effective Are Electronic Reputation Mechanisms? An Experimental Investigation," forthcoming, *Manage. Sci*.

Bulow, Jeremy and John Roberts. 1989. "The Simple Economics of Optimal Auctions," *J. Polit. Econ.* 97:5, pp.1060–90.

Cabral, Luis and Ali Hortaçsu. 2003. "Dynamics of Seller Reputation: Theory and Evidence from eBay," mimeo, U. Chicago.

Camerer, Colin. 1998. "Can Asset Markets Be Manipulated? A Field Experiment with Racetrack Betting," *J. Polit. Econ.* 106:3, pp. 457–82.

Cohen, Adam. 2002. *The Perfect Store: Inside eBay*. Little Brown & Co.

Coppinger, Vicki; Vernon Smith and Jon Titus. 1980. "Incentives and Behavior in English, Dutch and Sealed-Bid Auctions," *Econ. Inquiry* 43, pp. 1–22.

Cox, James C.; Bruce Roberson and Vernon Smith. 1982. "Theory and Behavior of single object auctions," *Res. Exper. Econ.* Vernon L. Smith, ed. JAI Press.

Coy, Peter. 2002. "Going, Going, Gone…Sucker!," *Bus. Week*, March 20.

Dellarocas, Chrysanthos. 2002. "The Digitization of Word-of-Mouth: Promise and Challenges of Online Reputation Mechanisms," *Manage. Sci*.

Dewan, Sanjeev and Vernon Hsu. 2001. "Trust in Electronic Markets: Price Discovery in Generalist Versus Specialty Online Auctions," mimeo, U. Washington Bus. School.

Eaton, David H. 2002. "Valuing Information: Evidence from Guitar Auction on eBay," mimeo, Murray State U.

Ederington, Louis H. and Michael Dewally. 2003. "A Comparison of Reputation, Certification, Warranties, and Information Disclosure as Remedies for Information Asymmetries: Lessons from the On-Line Comic Book Market," work. paper, Price College Bus., U. Oklahoma.

Elyakime, Bernard; Jean-Jacques Laffont; Patrice Loisel and Quang Vuong. 1994. "First price sealed bid auctions with secret reservation price," *Annales d'Econ. Statist.* 34, pp. 115–41.

Epple, Dennis. 1987. "Hedonic Prices and Implicit

Markets: Estimating Demand and Supply Functions for Differentiated Products," *J. Polit. Econ.* 95:1, pp. 59–80.

Ericson, Richard and Ariel Pakes. "Markov Perfect Industry Dynamics: A Framework for Empirical Work," *Rev. Econ. Stud.* 62, pp. 53–82.

Garratt, Rod; Mark Walker and John Wooders. 2002. "Experienced Bidders in Online Second-Price Auctions." work. paper, U. Arizona.

Haile, Philip; Han Hong and Matthew Shum. 2000. "Nonparametric Tests for Common Values in First-Price Auctions," mimeo, Yale U.

Hansen, Robert. 1986. "Sealed Bid Versus Open Auctions: The Evidence," *Econ. Inquiry* 24, pp. 125–14.

Harstad, Ronald; John Kagel and Dan Levin. 1990. "Equilibrium Bid Functions for Auctions with an Uncertain Number of Bidders," *Econ. Letters* 33, pp. 35–40.

Hasker, Kevin; Raul Gonzalez and Robin Sickles. 2003. "An Analysis of Strategic Behavior and Consumer Surplus in eBay Auctions," work. paper, Rice U.

Holt, Charles. 1980. "Competitive Bidding for Contracts under Alternative Auction Procedures," *J. Polit. Econ.* 88, pp. 433–45.

Hopenhayn, Hugo. 1992. "Entry, Exit, and Firm Dynamics in Long Run Equilibrium," *Econometrica* 60, pp. 1127–50.

Houser, Dan and John Wooders. 2003. "Reputation in Auctions: Theory and Evidence from eBay," work. paper, U. Arizona.

Ivanova-Stenzel, Radosveta and Tim Salmon. 2003. "Bidder Preferences Among Auction Institutions," *Econ. Inquiry*.

Jin, Ginger Z. and Andrew Kato. 2002. "Blind Trust Online: Experimental Evidence from Baseball Cards," work. paper, U. Maryland.

Kagel, John H.; Ronald M. Harstad and Dan Levin. 1987. "Information Impact and Allocation Rules in Auctions with Affiliated Private Values: A Laboratory Study," *Econometrica* 55, pp. 1275–304.

Kagel, John and Alvin Roth, eds. 1995. *The Handbook of Experimental Economics*. Princeton: Princeton U. Press.

Kalyanam, Kirthi and Shelby McIntyre. 2001. "Returns to Reputation in Online Auction Markets," mimeo, Leavey School Bus., Santa Clara U.

Katkar, Rama and David Lucking-Reiley. 2000. "Public versus Secret Reserve Prices in eBay Auctions: Results from a Pokémon Field Experiment," work. paper, U. Arizona.

Katok, Elena and Anthony Kwasnica. 2000. "Time Is Money: The Effect of Clock Speed and Seller's Revenue in Dutch Auctions," work. paper, Penn State U.

Kazumori, Eichiro and John McMillan. 2003. "Selling Online Versus Live," work. paper , CalTech and Stanford GSB.

Klemperer, Paul. 1999. "Auction Theory," *J. Econ. Surveys* 13:3, pp. 227–86.

Krishna, Vijay. 2002. *Auction Theory*. San Diego: Academic Press.

Ku, Gillian; Deepak Malhotra and J. Keith Murnighan. 2003. "Competitive Arousal in Live and Internet Auctions," work. paper, Kellogg Grad. School Manage., Northwestern U.

Levin, Dan and James L. Smith, J. L. 1994. "Equilibrium in Auctions with Entry," *Amer. Econ. Rev.* 54, pp. 585–99.

Li, Huagang and Goufu Tan. 2000. "Hidden Reserve Prices with Risk Averse Bidders," mimeo, Penn State U.

Livingston, Jeffrey. 2002. "How Valuable is a Good Reputation? A Sample Selection Model of Internet Auctions," mimeo, U. Maryland.

Lucking-Reiley, David. 1999a. "Using Field Experiments to Test Equivalence Between Auction Formats: Magic on the Internet," *Amer. Econ. Rev.* 89:5, pp. 1063–80.

———. 1999b. "Experimental Evidence on the Endogenous Entry of Bidders in Internet Auctions," work. paper, U. Arizona.

———. 2000a. "Vickrey Auctions in Practice: From Nineteenth-Century Philately to Twenty-First-Century E-Commerce," *J. Econ. Perspect.* 14:3, pp. 183–92.

———. 2000b. "Auctions on the Internet: What's Being Auctioned, and How?" *J. Indust. Econ.* 48:3, pp. 227–52.

Lucking-Reiley, David; D. Bryan; N. Prasad and D. Reeves. 2000. "Pennies from eBay: the Determinants of Price in Online Auctions," work. paper, U. Arizona.

Lucking-Reiley, David and Daniel F. Spulber. 2001. "Business-to-Business Electronic Commerce," *J. Econ. Perspect.* 15:1, pp. 55–68.

Matthews, Steven. 1995. "Comparing Auctions for Risk Averse Buyers: A Buyer's Point of View," *Econometrica* 55, pp. 633–46.

McAfee, R. Preston. 1993. "Mechanism Design by Competing Sellers," *Econometrica* 61, pp. 1281–312.

McAfee, R. Preston and John McMillan. 1987. "Auctions and Bidding," *J. Econ. Lit.* 25:2, pp. 699–738.

———. 1992. "Bidding Rings," *Amer. Econ. Rev.* 82, pp. 579–99.

McAfee, R. Preston; D. Quan and D. Vincent. 2002. "How to Set Minimum Acceptable Bids, with an Application to Real Estate Auctions," *J. Ind. Econ.* 50, pp. 391–416.

McDonald, Cynthia G. and V. Carlos Slawson. 2002. "Reputation in an Internet Auction Market," *Econ. Inquiry* 40, pp. 633–50.

Melnik, Mikhail I. and James Alm. 2002. "Does a Seller's eCommerce Reputation Matter? Evidence from eBay Auctions," *J. Ind. Econ.* 50, pp. 337–50.

Milgrom, Paul and Robert Weber. 1982. "A Theory of Auctions and Competitive Bidding," *Econometrica* 50, pp. 1089–122.

Morgan, John and Tanjim Hossain. 2003. "A Test of the Revenue Equivalence Theorem using Field Experiments on eBay," work. paper, Haas Bus. School.

Myerson, Roger. 1981. "Optimal Auction Design," *Math. Operation Res.* 6, pp. 58–73.

Ockenfels, Axel and Alvin E. Roth. 2003. "Late and Multiple Bidding in Second Price Internet Auctions: Theory and Evidence Concerning Different Rules for Ending an Auction," forthcoming, *Games Econ. Behav*.

Paarsch, Harry. 1992. "Deciding between the Common and Private Value Paradigms in Empirical Models of Auctions," *J. Econometrics* 51, pp. 191–215.

Park, Sangin. 2002. "Website Usage and Seller's Listing in Internet Auctions," work. paper, SUNY Stony Brook.

Peters, Michael and Sergei Severinov. 1997. "Competition among Sellers Who Offer Auctions Instead of Prices," *J. Econ. Theory* 75, pp. 141–79.

———. 2001. "Internet Auctions with Many Traders," work. paper, U. Wisconsin.

Rasmusen, Eric. 2001. "Strategic Implications of Uncertainty over One's Own Private Value in Auctions," work. paper, Indiana U.

Resnick, Paul and Richard Zeckhauser. 2001. "Trust Among Strangers in Internet Transactions: Empirical Analysis of eBay's Reputation System," work. paper, Harvard Kennedy School.

Resnick, Paul; Richard Zeckhauser, John Swanson and Kate Lockwood. 2003. "The Value of Reputation on eBay: A Controlled Experiment," work. paper, Harvard Kennedy School Gov.

Rezende, L. 2003. "Auction Econometrics by Least Squares," mimeo, U. Illinois Urbana-Champlain.

Riley, John and William Samuelson. 1981. "Optimal Auctions," *Amer. Econ. Rev.* 71, pp. 381–92.

Robinson, Marc. 1985. "Collusion and the Choice of Auction," *Rand J. Econ.* 16, pp. 141–45.

Rosen, Sherwin. 1974. "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition," *J. Polit. Econ.* 82:1, pp. 34–55.

Roth, Alvin E. and Axel Ockenfels. 2002. "Last-Minute Bidding and the Rules for Ending Second-Price Auctions: Evidence from eBay and Amazon Auctions on the Internet," *Amer. Econ. Rev.* 92:4, pp. 1093–103.

Schindler, Julia. 2003. "Late Bidding on the Internet," mimeo, Vienna U. Econ. and Bus. Admin.

Vickrey, William. 1961. "Counterspeculation, Auctions and Competitive Sealed Tenders," *J. Finance* 16, pp. 8–37.

Vincent, Daniel. 1995. "Bidding Off the Wall: Why Reserve Prices May Be Kept Secret," *J. Econ. Theory* 65, pp. 75–84.

Wang, Joseph. 2003. "Is Last Minute Bidding Bad?" work. paper, UCLA.

Wilcox, Ronald T. 2000. "Experts and Amateurs: The Role of Experience in Internet Auctions," *Markeing Letters* 11;4, pp. 363–74.

Wilson, Robert. 1977. "A Bidding Model of Perfect Competition," *Rev. Econ. Stud.* 44, pp. 511–18.

Wolverton, Troy. 1999. "eBay Users Miffed by New Fees," CNET News.com, Aug. 20.

Yin, Pai-Ling. 2003. "Information Dispersion and Auction Prices," work. paper, Harvard Bus. School.