Reputation in Auctions: Theory, and Evidence from eBay*

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Abstract

We model auctions in which bidders and the seller have observable and heterogenous reputations for defaulting on an auction contract. Employing a simple procedure suggested by our theoretical results, we examine the effect of reputation on price in a data set drawn from the online auction site eBay. Our main empirical result is that seller, but not bidder, reputation has an economically and statistically significant effect on price.

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1 Introduction

The Internet has dramatically lowered the costs of organizing markets. In the case of auction markets, search engines allow bidders who are widely dispersed geographically to identify auctions of interest easily; online bids are submitted with little hassle; the current status of an auction is easily observed by all participants; the auction itself is automated and is run at virtually no cost by the host. As a result, there are now hundreds of web sites hosting online auctions, with Amazon.com, Yahoo! auctions, and eBay.com the main consumer-to-consumer auction sites. In the fourth quarter of 2000, eBay, the leader in online consumer auctions, hosted nearly 80 million auctions with $1.6 billion of goods trading on the site.

With the growth of online markets comes an increasing need for bidders and sellers to engage in transactions with counterparts with whom they have had little or no previous interaction. This introduces risks to traders. The winner of the auction might not deliver payment, the seller might not deliver the good, or the good delivered might not be as the seller described. These risks are a significant obstacle to the further growth of online markets with, according to the Federal Trade Commission, the number of consumer complaints about Internet auctions "exploding" in the last year.[1] Further, 78 percent of all Internet fraud complaints received by the National Consumers League in 2000 were related to online auctions.[2]

One of the principle means by which online auction sites mitigate these risks is by maintaining feedback forums. Amazon, Yahoo! auctions, and eBay all allow bidders and sellers to leave feedback about each other following a transaction. The collection of comments left for a particular user becomes the user's feedback profile, and forms a public record of the user's performance in prior transactions. A potential bidder on a item, for example, can view all the comments left for the seller by other users. He can learn whether the seller has consistently delivered the item to the winning bidder, and whether he accurately describes the item for sale. Hence, feedback profiles become a

[1] Federal Trade Commission press release, February 14, 2000 (http://www.ftc.gov/opa/2000/02/internetauctionfraud.htm).

[2] See http://www.natlconsumersleague.org/.

means by which honest sellers can (eventually) be distinguished from dishonest ones. Furthermore, if sellers obtain higher prices as their feedback profile is more positive, then the existence of feedback forums themselves provides a positive incentive to sellers for good performance.[3]

Reputation has long been of interest to economists. Kreps and Wilson (1982) use reputation to resolve Selten's Chain-Store paradox. Kreps, Milgrom, Roberts, and Wilson (1982) use reputation to explain the cooperation observed in experimental studies of the finitely repeated Prisoners' dilemma game. Shapiro (1983) shows that when quality is unobservable then firms with a reputation for producing good quality products enjoy a pricing premium; this premium makes it optimal for a firm to continue producing good quality products, thereby maintaining its reputation, rather than making a short term gain by reducing quality. Despite the importance of reputation in theoretical models, empirical work has been hampered by a lack of data.

The rise of feedback forums at online auction sites provides a unique new opportunity to test whether reputation affects market outcomes. The present paper develops a theoretical model of consumer-to-consumer auctions with "proxy bidding," when traders face the risk that their counterpart may default on the auction contract, and when traders have observable and heterogeneous reputations for default.[4] Our theoretical results suggest a simple procedure to quantify the importance of bidder and seller reputations on auction prices. We use this procedure to examine reputation effects in a data set drawn from eBay.

In our theoretical model a bidder's reputation is represented by the probability that, if he wins the auction, he will deliver payment. The seller's reputation is

[3]For an introduction to the various ways in which reputation systems facilitate trade in otherwise anonymous settings, see Resnick, Zeckhauser, Friedman, and Kuwabara (2000).

[4]Default in auctions has received only limited theoretical attention, in models with homogeneous bidders. Waehrer (1995) studies the effect on seller revenue of requiring buyers to post deposits which are forfeit in the event of default. In a common-values setting, Harstad and Rothkopf (1995) show that allowing bid withdrawal (perhaps with the payment of a penalty) can enhance seller revenue.

represented by the probability that, once he receives payment, he will deliver the item auctioned. Since we study auctions where a trader's reputation, that is, his feedback profile, is publicly observable, we assume these probabilities are commonly known to all traders. In contrast, we assume that each bidder is privately informed of his own value. We establish the (intuitive) result that the equilibrium proxy bid of the bidder with the second-highest value equals his expected value of winning the auction. This expected value depends upon the seller's reputation, but does not depend upon his own or the other bidders' reputations. This result is the foundation of our empirical analysis of reputation effects.

Our theoretical results suggest that seller (but not bidder) reputation affects price. In the empirical portion of this paper we first quantify the importance of seller reputation in consumer-to-consumer auctions. To do this we construct an empirical model based on our model of consumer auctions. We then take the model to a dataset that we constructed from auctions held on eBay of Intel Pentium III 500 megahertz processors (PIII 500's) during the fall of 1999. Our main result is that bidders pay a statistically and economically significant premium to sellers with better reputations. This result provides empirical support for Shaprio's (1983) theoretical finding of a positive relationship between reputation and price. We also examine the effect of bidder reputation on price and find that the effect is statistically insignificant, which is consistent with our model.

The paper is organized as follows: In Section 2 we describe some institutional detail for online consumer-to-consumer auctions. Readers familiar with eBay auctions may wish to skip this section. Our model, results, and empirical methods are presented in Section 3. Section 4 discusses our data, Section 5 presents our empirical results, and Section 6 concludes. All proofs are in the Appendix.

2 Consumer-to-Consumer Auctions: Background

Before presenting our models and empirical work it is useful to describe the key features of Internet consumer-to-consumer auctions. Our discussion will focus on eBay single-unit auctions since they are representative of consumer-to-consumer auctions and since our empirical work uses eBay data. We discuss the listing of items for sale, proxy bidding, default, and eBay's feedback system.

Listing Items

To list an item for sale the seller enters an auction category (e.g., `Collectibles>Pez>Current`), the description and location of the item, the shipping cost, the minimum bid, the (secret) reserve price if any, and the duration of the auction (3, 5, 7 or 10 days).[5] The seller pays eBay an insertion fee which depends on the opening or reservation price; the seller also pays a fee based on the final price. For an item which is listed with an opening bid of $0.01, without a reserve, and which sells for $245 (approximately the mean price in our data), the listing fee is $0.25 and the final value fee is $6.75.

Bidding

Auctions of a single item are conducted as ascending-price auctions with "proxy" bidding. As eBay describes proxy bidding, a bidder enters the maximum amount that he is willing to bid, and then "The system will bid for you as the auction proceeds, bidding only enough to outbid other bidders. If someone outbids you, the system immediately ups your bid. This continues until someone exceeds your maximum bid, or the auction ends, or you win the auction!"

Consider, for example, an auction in which the minimum bid is $1.00 and there is no reserve. If the first bidder to enter a bid is Bidder A and he enters a proxy bid of $10.00, then Bidder A has the high bid, and the high bid is $1.00. (A bidder considering whether to bid only observes the high bid and the user ID of the bidders who have already bid.) The new minimum bid is the high bid plus the bid increment (the increment is $.05 when the high-bid is $1.00). Suppose Bidder B enters a proxy bid of $6.00. Bidder B is immediately outbid by eBay which, acting on Bidder A's behalf, increases his bid to $6.00 plus the minimum bid increment (now $0.50). The new minimum bid is $7.00. If Bidder C enters a proxy bid of $15.00, then Bidder A is outbid, and Bidder C has the high bid of $10.50. If there are no further bids by

[5] A reserve price is the lowest price at which the seller is willing to sell the item.

the time the auction ends, then Bidder C wins the item and he pays \$10.50, plus the shipping costs indicated in the description of the item.

In auctions with a reserve, if all the proxy bids are less than the reserve, then the high bid is just the second-highest proxy bid plus the bid increment. If one or more of the proxy bids are above the reserve, then the high bid is the maximum of (i) the second-highest proxy bid plus the bid increment, or (ii) the reserve. Suppose in the example just discussed that there was a reserve of \$12.00. If Bidder A bids \$10.00, then as before Bidder A has the high bid (of \$1.00) and the reserve has not been met. If Bidder B bids \$6.00, then Bidder A still has the high bid (now of \$6.50) and the reserve is still not met. If Bidder C bids \$15, then Bidder C has the high bid of \$12.00, equal to the reserve price, which is now met.

A bidder may increase his proxy bid at any time (perhaps because he is outbid), but his new proxy bid must always equal at least the current minimum bid. If the auction has not yet ended, eBay's rules also allow a bidder to retract his bid. At the end of an auction, the seller and the winning bidder exchange email to confirm the outcome of the auction and to discuss arrangements for completing the transaction. The bidder pays the seller first and the seller then ships the item.

Default

According to eBay, the auction contract between a seller and the winning bidder is binding. eBay, however, does not enforce individual contracts, although it will suspend sellers who exhibit "chronic nonperformance." Similarly, according to eBay "Bidding without paying for items bid on in a chronic, habitual manner" is a bidding offense and can lead to a warning or suspension for a bidder.[6] As we discuss below, negative feedback from other eBay users can also lead to suspension.

Feedback

Each eBay user has a feedback profile consisting of comments left by other users.

[6] Neither eBay nor the other main consumer-to-consumer auction sites provide a way for bidders to post a deposit or pay a penalty in the event of default.

An example of a feedback profile is given in Figure 1.

Figure 1 goes here.

Each comment is classified by the poster as either positive, neutral, or negative with scores of +1, 0, and -1, respectively. These scores are added to give an overall feedback score. (The user in Figure 1 has a score of $256 = 258 - 2$.) Only comments from unique users are used in computing overall feedback scores. A user whose feedback score falls to -4 is automatically suspended from eBay.

Until recently, any eBay user could leave feedback about another user, whether or not they had completed a joint transaction (except for negative feedback which had to be transaction related). Currently eBay requires all feedback to be transaction related. Some typical positive, neutral, and negative comments are displayed in Figure 2.

Figure 2 goes here.

3 Theoretical and Empirical Models

We model auctions in which traders may default on the auction contract and where each trader evaluates the risk of default on the basis of his counterpart's reputation. There is a single seller and n bidders. The seller has a single unit of an indivisible good for auction, with cost normalized to zero. Bidder i's value is denoted by v_i, with $v_i > 0$, and is privately known. (Later we shall discuss why our independent-values framework is appropriate for Pentium processor auctions, despite the fact that processors may be purchased retail.) The seller's reputation is given by a probability $r^S \in (0, 1]$ that the seller delivers the item once he has received payment. Bidder i's reputation is described by a probability $r_i^B \in (0, 1]$ that bidder i delivers payment when he wins the auction. Reputations are assumed to be commonly known. In our empirical analysis, we will assume that these probabilities are functions of the bidders' and sellers' public feedback profiles.

If bidder i wins the auction and is to pay the price b, then with probability r_i^B he delivers payment and his expected payoff is $(r^S v_i - b)$; with probability $(1 - r_i^B)$ he defaults and his payoff is zero. His expected utility, therefore, is

$$r_i^B(r^S v_i - b).$$

The payoff of every non-winning bidder is zero. Here we have not modeled the bidder's decision to default, but it is straightforward to do so.[7]

Consumer-consumer auctions are dynamic games of incomplete information. Since only the bidders' final proxy bids are observed in eBay bid histories, our approach here, rather than to explicitly model the dynamics, is to develop a reduced-form model which identifies equilibrium final bids.

In the auction, bidders choose "proxy" bids. If $(b_1, \ldots, b_n)$ is a profile of proxy bids, then we say that **bidder i has the high bid** if $b_i \geq b_j \ \forall j \neq i$, i.e., if he has the highest proxy bid. If bidder i has the high bid, we say that the **high bid** is equal to $\max_{k \neq i} b_k$, i.e., the high bid is the second-highest proxy bid. In the course of the auction, each bidder observes only the amount of the high bid. To change his proxy bid, a bidder's new bid must be greater than the current high bid. We assume that a bidder who does not have the high bid is always able to increase his proxy bid before the auction ends.[8] The bidder who has the high bid when the auction ends wins the auction, and he pays the high bid.

We now identify the conditions that a terminal profile of proxy bids must satisfy. Suppose $(b_1, \ldots, b_n)$ is a profile of proxy bids. If there are no further bids, then the

[7] Rational bidder default can be modelled as follows: Assume that bidder i's value in the auction is given by $v_i X_i$,where X_i is a binomially-distributed random variable, with $X_i = 1$ with probability r_i^B and $X_i = 0$ otherwise. (As before, each bidder i is privately informed of v_i. Each bidders i's reputation r_i^B, and hence each distribution X_i, is commonly known.) Before making payment, but after the auction terminates, bidder i privately observes x_i, the realized value of X_i. If bidder i wins the auction with a bid of b he optimally defaults when $b > v_i x_i$. Hence, as above, his expected payoff is $r_i^B(r^S v_i - b)$. This model is a simple way to capture the idea that a bidder may not value the item at the end of the auction, in which case he defaults. See Waehrer (1995) for a similar model of default.

[8] Like Roth and Ockenfels (2000) we also observe a tendency for late bidding. However, for the auctions in our data set, the median time between when the winning bid was placed and the end of the auction is 284 minutes. Hence a bidder who did not win the auction generally did have time to revise his bid.

winner of the auction is the bidder i with the high bid, i.e., the bidder i for whom

$$b_i = \max_k b_k. \tag{1}$$

Consider a bidder j who does not have the high bid. For bidder j to change his proxy bid, his new proxy bid must exceed the high bid, i.e., his new proxy bid $\hat{b}_j$ must satisfy $\hat{b}_j > \max_{k \neq i} b_k$. Bidding will terminate only if, for each bidder $j \neq i$, even the smallest such bid is more than bidder j's expected value $r^S v_j$ of winning the auction, i.e.,

$$\max_{k \neq i} b_k \geq r^S v_j \;\forall j \neq i. \tag{2}$$

Finally, a profile of terminal proxy bids $(b_1, \ldots, b_n)$ must satisfy

$$b_j \leq r^S v_j \;\forall j, \tag{3}$$

since no bidder will ever bid above his expected value.

Combining conditions (1)-(3), we obtain a definition of equilibrium.

Definition: An equilibrium is a pair $\{(b_1^*, \ldots, b_n^*), i^*\}$, where $(b_1^* \ldots, b_n^*)$ is a profile of proxy bids and bidder i^* is the winning bidder, such that

$$\begin{array}{llcll} \text{(i)} & b_{i^*}^* & = & \max_k b_k^* & \\ \text{(ii)} & \max_{k \neq i^*} b_k^* & \geq & r^S v_j & \forall\, j \neq i^*. \\ \text{(iii)} & b_j^* & \leq & r^S v_j & \forall j. \end{array}$$

Proposition 1, which follows, establishes the intuitive result that in every equilibrium of the auction (i) the bidder with the highest value wins the auction, and (ii) he pays the expected value of winning the auction for the bidder with the second-highest value. It also establishes that it is an equilibrium for every bidder to bid his expected value of winning the auction (so an equilibrium exists).

To simplify the statement of Proposition 1, we ignore the possibility that two or more bidders have the same value, and relabel the bidders so that $v_1 > v_2 > \ldots > v_n$.

Proposition 1: If $\{(b_1^*, \ldots, b_n^*), i^*\}$ is an equilibrium, then (i) $i^* = 1$ and (ii) $\max_{k \neq 1} b_k^* = b_2^* = r^S v_2$. Furthermore, $\{(b_1^*, \ldots, b_n^*), 1\}$ is an equilibrium, where $b_j^* = r^S v_j \;\forall j$.

The proposition allows that bidders (other than the bidder with the second-highest value) may bid less than their expected value of winning the auction. This is consistent with eBay auctions where, before a bidder is able to revise his proxy bid, subsequent bids by other bidders may raise the high bid above his expected value of winning the auction. In this case, the bidder's last proxy bid (which is the bid observed in eBay bid histories) may be less than his expected value of winning.

Empirical Method

By Proposition 1, in equilibrium the second-highest bid in auction i, denoted by b^*_{i2}, is given by

$$b^*_{i2} = r_i^S v_{i2},$$

where v_{i2} is the second-highest bidder's value for the item in auction i and r_i^S is the reputation of the seller in auction i. It follows that

$$\log(b^*_{i2}) = \log(r_i^S) + \log(v_{i2}). \tag{4}$$

Our interest is in implementing (4) empirically, which requires one to posit a relationship between a seller's observable characteristics and their reputation r_i^S, and between the item in auction i and the value v_{i2}.

We assume that all bidders evaluate seller i's reputation according to the following:

$$r_i^S = \lambda x_{i1}^{\theta_1} x_{i2}^{\theta_2} \cdots x_{iK}^{\theta_K}, \tag{5}$$

where λ is a positive scalar, $x_i = (x_{i1}, \ldots, x_{iK})$ is a positive real vector of observable characteristics that affect seller i's reputation, and $(\theta_1, \ldots, \theta_K)$ is a real vector.

Our model for v_{i2} is:

$$v_{i2} = \phi y_{i1}^{\pi_1} y_{i2}^{\pi_2} \cdots y_{iM}^{\pi_M} e^{\eta_{i2}}, \tag{6}$$

where ϕ is a positive scalar, $y_i = (y_{i1}, \ldots, y_{iM})$ is a positive real vector of characteristics of the item in auction i, $(\pi_1, \ldots, \pi_M)$ is a real vector, η_{i2} is a real random variable and $e^{\eta_{i2}}$ provides the idiosyncratic influence on value for the bidder with the second-highest bid in auction i. We assume that the idiosyncratic value draws are *i.i.d.* Note that differences in bids in auction i are due entirely to different realizations of η_i. As a result, the bidder with the second-highest value in auction i also has the second-highest idiosyncratic value draw.

The second-highest idiosyncratic value η_{i2} is an order statistic. Its density depends on the underlying density of the η_i's as well as the number of bidders in the auction. In the theory, the number of bidders is the number of decision makers who are aware of the auction, who are able to bid, and who have a value for the item. The best measure of the number of bidders in an eBay auction might be the number of users who click on the link to the auction's main page.[9] Unfortunately, this is not observable in the data; one only observes the number of bids actually placed.[10] Therefore, we assume that the number of bidders in auction i is a nonstochastic function of the auction's length t_i. Hence, the density of η_{i2} varies with t_i. We assume that this density has first and second moments for all possible t_i.

It is useful to rewrite equation (4) in a more convenient form. Defining $\varepsilon_{i2} = \eta_{i2} - E(\eta_{i2}|t_i)$, then ε_{i2} has mean zero and a variance that depends on t_i. Combining our assumptions about the error process with (5) and (6), we obtain the following empirical model of auction i's second-highest bid:

$$\begin{aligned} \log(b^*_{i2}) &= c + \widetilde{x}'_i\theta + \widetilde{y}'_i\pi + \alpha_{t_i} + \varepsilon_{i2}, \\ E(\varepsilon_{i2}) &= 0,\ Var(\varepsilon_{i2}) = \sigma^2_{t_i}, \end{aligned} \tag{7}$$

where $\alpha_{t_i} = E(\eta_{i2}|t_i)$, c is a constant equal to $\log(\lambda) + \log(\phi)$, and $\widetilde{x}'_i$ and $\widetilde{y}'_i$ represent vectors of logs of the elements of x_i and y_i.

Let ε_2 denote the vector of residuals associated with the system formed by stacking equations (7) according to auction length, and suppose that there are N different auction lengths observed in total and k_n auctions of each length n. Under the assumption

[9] The link to an auction's main page gives no indication of the seller's reputation, hence the number of bidders, naturally defined this way, is uncorrelated with the seller's reputation.

[10] A bidder will only place a bid if his value for the item exceeds the high bid when he first views the auction. Hence the number of bidders is generally larger than the number of bids placed.

that all idiosyncratic value draws are independent, the residual vector satisfies

$$E(\varepsilon_2) = 0,\ E(\varepsilon_2 \varepsilon_2^{'}) = \begin{bmatrix} \sigma^2_{Length_1} I_{k_1} & 0 & \cdots & 0 \\ 0 & \sigma^2_{Length_2} I_{k_2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma^2_{Length_N} I_{k_N} \end{bmatrix},$$

where $\sigma^2_{Length_n}$ is the variance of the residuals in auctions of length k_n and I_{k_n} is the identity matrix of dimension k_n. Accordingly, under standard regularity conditions, consistent and asymptotically efficient estimates for the parameters of the system can be obtained through generalized least-squares procedures.[11]

4 Evidence from eBay

Our empirical analysis is based on auctions of Pentium III 500 processors held on eBay during the fall of 1999. We study auctions on eBay, rather than auctions on one of the many other auction sites, because eBay is the leading online auction market.

Processor auctions provide an excellent environment to study reputation effects for a number of reasons. First, PIII 500's processors are homogeneous.[12] Hence, the price variation observed in auctions can be traced to variation in the trader's reputations, and to random variation in bidder values, and not to variation in the good being auctioned.[13] Second, PIII 500 processors are fairly high-value items. Therefore, the failure of a seller to deliver the item will not be inconsequential to the bidder. It

[11] Since the winning bid on an eBay auction differs from the second highest bid only by the bid increment, our work also provides a theoretical justification for the first price regressions used in Lucking-Reiley et al. (1999).

[12] PIII 500's are available in a retail package and an OEM (original equipment manufacturer) package. The retail package comes with a three-year warranty, a heat sink, and a fan. The OEM package provides only a 90 day warranty and comes without a heatsink or fan. A small fraction of the processors in our data set are also listed as being "used" rather than new.

[13] Lucking-Reiley et al.'s (1999) study of the effect of reputation in collectible coin auctions is complicated by the need to control for different coins having different book values. In an empirical study of endogenous entry in eBay coin auctions, Bajari and Hortaçsu (1999) adopt a common-values framework.

seems more likely that the traders' reputations will matter in such settings.

It seems unlikely that processors are purchased on eBay for resale since (unlike collectible coins, say) processor prices tend to fall over the long term. Bidders of Pentium processors who are planning to build or upgrade a computer are likely to be well informed about retail prices for processors. Hence, bidding is unlikely to convey information about retail prices. This is especially true since over the period of time our data were collected, retail prices for PIII 500 processor were quite stable. These facts all suggest that our independent private-values model, and not a common-values model, is appropriate for this data set.[14]

Data Collection Procedure

We collected our data by hand from eBay's website. First, under the category `Hardware>CPUs>Intel` we searched eBay (using the search tool they provide on their web site) for auctions containing the keywords "Pentium III 500." This took us to a page listing current auctions containing this keyword. We then followed a link on this page to a list of auctions that were completed in the last two weeks. Some of the auctions were not relevant since they were auctions for whole systems or system motherboards. For each of the auctions which were for a single processor only, from the main auction page we recorded the user ID of the seller and the winning bidder, the high bid, whether there was a reserve, the minimum bid, the amount of the shipping costs, and the start and end time of the auction. We then followed a link on the main page to the auction's bid history. From this page, we recorded the second-highest bid and the user ID of the bidder with the second-highest bid. We repeated this entire procedure for the keyword "Pentium III 500mhz." In total we obtained data for 95 auctions on eBay for single PIII 500's, with closing dates between September 23, 1999 and December 18, 1999.[15]

The main and bid history pages provide us with most of the data that we need

[14] Our argument that a private-values framework is appropriate even though processors may be purchased retail is similar to Paarsch's (1997) argument that private values are appropriate in timber auctions even though logs are sold after harvest.

[15] One auction was lost due to a recording error, and could not be recovered since auctions more than two weeks old do not appear on searches of completed auctions.

for our empirical analysis. But, for two reasons, they do not provide the information we need about reputation. First, these pages only report a user's overall feedback score. To obtain a more detailed measure of each user's reputation, we followed the link (next to his ID) to a page containing the user's feedback profile. Second, eBay updates feedback profiles in real time and so a user's profile at the time we collect this data will not be the same as his profile at the time the auction ended if, in the interim, he has received additional feedback. However, each item of feedback contains the date it was posted and, since we know the time at which each auction in our data set closed, it is straightforward, although tedious, to calculate the number of positive, negative, and neutral comments from unique users at the time the auction closed. These are the data we use for reputation in our empirical analysis.

Variables used in Empirical Analysis

The dependent variable, denoted by *SecondPrice,* is the second-highest bid plus the shipping cost indicated in the description of the item.[16] It turns out that in our data set there is at least one bid in every auction, and there were two or more bids in all but one auction. Since the second price is not observed in this last auction our results are based on the 94 auctions that remain after this auction is dropped.

The seller reputation variables are: *Shades*, *PosRep*, *NeutRep*, and *NegRep.* The *shades* variable is a dummy variable, taking the value one if the seller has a "shades" icon next to his user ID. (The icon indicates that the user has, in the last 30 days, either registered on eBay for the first time or changed his user ID.) The variables *PosRep*, *NeutRep*, and *NegRep* are, respectively, the number of positive, neutral, and negative comments from unique registered users in the seller's feedback profile.

The variables which define the characteristics of the item are: *MarketPrice*, *Visa*, *Used*, and *Retail.* The variable *MarketPrice* is a measure of PIII 500 retail prices and does not include shipping costs. It is included since a bidder's value in an auction for a processor will be depend on the processor's retail prices. We obtained retail price data from CPUReview.com which provides, bi-monthly, the lowest advertised

[16] We include shipping costs since we define the item as a Pentium III 500 delivered to the winning bidder.

price on Pricewatch.com. These prices are for a single PIII 500 processor in an OEM package, and do not include shipping costs. The other three variables are dummy variables. *Visa* takes the value one if the seller accepts payment by credit card. It is included since a bidder's value for the item might depend upon whether he can dispute the seller's charge if the seller fails to deliver it. *Used* takes the value one if the processor is listed as used and zero otherwise. *Retail* takes the value one for the retail version of the processor, and zero otherwise.[17] A processor can be both used and retail if, for example, it is described as "used only for a day" and "comes in original packing with full warranty."

The remaining variables defining the auction's characteristics are: *Exclude*, *Len5*, *Len7*, and *Len10*. These are all dummy variables, with *Exclude* taking the value one if the seller excludes low-reputation bidders, and zero otherwise. We classify a seller as an excluder if the main auction page contained a statement that bids from low-reputation bidders would be cancelled, or if he was observed to cancel a bid from a low-reputation bidder. The variable *Len5* takes the value one for a 5 day auction, and zero otherwise. *Len7* and *Len10* are defined similarly.

Summary Statistics

Table 1 provides summary statistics for the variables used in our analysis.

Table 1 goes here.

The second price ranged from a high of \$303 to a low of \$205 and tended to be higher earlier in our sample period. Our measure of the market price ranged more narrowly from \$229 to \$215. The variation in the number of positive comments received by sellers is much larger than the variation in either neutral or negative comments. One seller in our data set had 1090 positive comments. More than one third of the sellers

[17] In eight auctions the seller did not characterize the chip as either used or new. The "used" dummy was set to zero for these observations. In 24 auctions the seller did not indicate whether the chip was retail or OEM. The "retail" dummy is set to zero in each of these cases. This labelling implies that bidders assume a processor is equivalent to a new OEM processor unless they are informed otherwise. Alternative classifications for the ambiguous cases do not change the nature of our inferences regarding reputation effects.

had only zero or one positive comment. The number of neutrals and negatives each range from zero to 12. In 13% of the auctions in our data set the seller excluded low-reputation bidders. The first and second most common auction lengths were 3 days (44%) and 7 days (33%).

Perhaps not surprisingly given its public good nature, feedback is often not left. In the 94 auctions in our data set, the number of positive, neutral, and negative comments left for sellers is 23, zero, and four respectively. The number of positive, neutral, and negative comments left for bidders is 24, one, and one, respectively. Hence, feedback was left for sellers in less than one-third of the auctions. All the neutral and negative comments related to default, with at least one seller failing to deliver the processor after having taken payment.

5 Results

Our findings derive from a standard two-step generalized least squares (GLS) procedure applied to the system formed by stacking equations (7). We initially specified the reputation characteristics $\widetilde{x}_j$ to include *shades*, $\log(1 + PosRep)$, $\log(1{+}NeutRep)$, and $\log(1{+}NegRep)$. However, we could not reject the null hypothesis that the coefficient of the latter two terms is the same (the *p*-value of the appropriate χ^2-test is 0.82). Hence, our discussion below is based on a seller reputation regressor matrix that includes *shades*, $\log(1{+}PosRep)$ and a third term *LogNonposRep* which is equal to the sum of $\log(1{+}NeutRep)$ and $\log(1{+}NegRep)$. The auction characteristics are the log of *MarketPrice,* and the dummy variables *Visa*, *Used*, *Retail, Exclude*, *Len5*, *Len7*, and *Len10* as discussed above.

Table 2 reports the results of our GLS analysis.

Table 2 goes here.

The three reputation variables have the expected signs and the coefficients for both positive and nonpositive comments are statistically significant. The coefficient of shades is extremely small in magnitude and statistically insignificant. This suggests that bidders do not perceive shades as providing any more information than is provided by the raw reputations. The coefficient estimates suggest that a ten percent increase in positive comments will increase, ceteris paribus, the winning price by about 0.17%. This is smaller in magnitude than the point estimate of the cost of a 10% increase in neutral or negative comments, which is a 0.24% price reduction. Reputation effects are economically significant. For example, increasing the number of positive comments from zero to 15 will, evaluated at point estimates and ceteris paribus, increase the final bid price by about 5% or around $12.

Among the variables that define the characteristics of the auction, only whether the processor is retail and *LogMarketPrice* are statistically significant. The results suggests that the retail package sells for about 5% more than the OEM package, a premium that is likely being paid for the extended warranty the retail package provides. Sellers who excluded bidders also seem to receive lower final prices. The length of the auction seems to have little effect on the final price. On the other hand, the estimated variance of ε_{i2} is smaller when the length of auction i is larger. This might mean that longer auctions attract more bidders, and this reduces the variability of the sale price.

From the estimates in Table 2 one can easily obtain estimates of the value that any seller's "stock" of positive reputation adds to their final sale price. After doing this for all of the auctions in our sample, it turns out that the distribution of the estimates has a mean of $8.46 and a standard deviation of $7.34. (One seller's positive score increased their sale price by over $24.) Hence, on average 3.46% of sales is attributable to the sellers' stock of positive reputation. If this percentage applied to all of eBay's auctions ($1.6 billion in the fourth quarter of 2000), this would imply that seller reputations added more than $55 million to the value of sales.

Bidder Reputations

Our model predicts that the second-highest bid should not depend upon the bidder's own reputation. A simple way to test this prediction is to augment our empirical model with bidder reputation covariates in order to examine their explanatory power.[18] To do this, we define bidder reputation variables exactly analogously to the seller reputation variables: *bidderPos* is the log of one plus the number of unique positive comments and *bidderNonPos* is the sum of the log of one plus the number of neutral comments and the log of one plus the number of negative comments. The results of a two-step generalized least squares procedure based on this augmented specification are provided in Table 3.

Table 3 goes here.

The results show that the coefficients on the bidder reputation variables are individually statistically insignificant. A χ^2-test of the null hypothesis that they are jointly zero cannot be rejected at standard significance levels (the p-value is 0.48). Furthermore, the original estimates reported in Table 2 do not change very much under the augmented specification. Hence, consistent with the theory, we find no evidence that bidders' reputations affect the second-highest bid for the processors in our data set.

6 Conclusion

The present research models bidding behavior in auctions when traders have heterogenous reputations for default. Our results provide a simple framework for the empirical analysis of the effect of reputation on auction prices. We built an empirical model to quantify the effect of reputation on prices in eBay Pentium III 500 auctions. Our main finding was that seller reputation (but not bidder reputation) is a statistically and economically significant determinant of auction prices.

There are several important issues that this paper has not addressed. One is reputation building in auctions. A seller who provides good service can look forward to positive feedback from the bidder and this enhances his reputation. Since sellers with better reputations get higher prices, the feedback system provides incentives for good performance by sellers. Similarly, a bidder who routinely delivers payment

[18] Of course, if bidders' reputations are correlated with their values, then this specification is inappropriate and will lead to biased and inconsistent parameter estimates.

in the auctions he wins will develop a good reputation and will not risk finding his bids cancelled due to a low feedback score. An investigation of how the mechanism for reputation building affects incentives for good performance in contracts is an important topic for future research.

Another important question is whether reputation is a good predictor of future performance. For example, are sellers with more positive feedback less likely to default than sellers with less positive feedback? Our finding that bidders pay more to sellers with better reputations suggests that bidders believe this is the case. eBay's data is rich enough to allow an investigation of this question.

7 Appendix

PROOF OF PROPOSITION 1: Let $\{(b_1^*, \ldots, b_n^*), i^*\}$ be an equilibrium and suppose that $i^* > 1$. Then

$$\begin{aligned} r^S v_1 &> r^S v_{i^*} && \text{by since } v_1 > \ldots > v_n \\ &\geq b_{i^*}^* && \text{by (iii)} \\ &\geq \max_{k \neq i^*} b_k^* && \text{by (i).} \end{aligned}$$

Hence $r^S v_1 > \max_{k \neq i^*} b_k^*$, which contradicts (ii) in the definition of equilibrium. This establishes $i^* = 1$.

We now establish Proposition 1(ii). By (iii) we have $b_2^* \leq r^S v_2$ and, since $v_2 > \ldots > v_n$, we have for $k > 2$ that $b_k^* \leq r^S v_k < r^S v_2$. Suppose that $b_2^* < r^S v_2$. Then $\max_{k \neq 1} b_k^* < r^S v_2$, which contradicts (ii). Hence $b_2^* = r^S v_2 = \max_{k \neq 1} b_k^*$, which completes the proof of Proposition 1(ii).

We now establish that $\{(b_1^*, \ldots, b_n^*), 1\}$, where $b_j^* = r^S v_j \; \forall j$, is an equilibrium. Since $v_1 > \ldots > v_n$ we have $b_1^* \geq b_j^* \; \forall j > 1$ and $\max_{k \neq 1} b_k^* = r^S v_2$. Hence $\max_{k \neq 1} b_k^* \geq r^S v_j \; \forall j > 1$. Condition (iii) in the definition of equilibrium is satisfied by construction. $\square$

References

[1] Bajari, P. and Hortaçsu, A. (1999): "Winner's Curse, Reserve Prices and Endogenous Entry: Empirical Insights from eBay Auctions," mimeo.

[2] Donald, S. and Paarsch, H. (1996): "Identification, Estimation, and Testing in Parametric Empirical Models of Auctions within the Independent Private Values Paradigm," *Econometric Theory* **12**, 517-567.

[3] Kreps, D. and Wilson, R. (1982): "Reputation and Imperfect Information," *Journal of Economic Theory* **27**, 253-279.

[4] Harstad, R. and Rothkopf, M. (1995): "Withdrawable Bids as Winner's Curse Insurance," *Operations Research* **43**, 983-994.

[5] Hendricks, K. and Paarsch, H. (1995): "A Survey of Recent Empirical Work Concerning Auctions," *Canadian Journal of Economics* **28**, 403-426.

[6] Kreps, D., Milgrom, P., Roberts, J., and Wilson, R. (1982): "Rational Cooperation in the Finitely Repeated Prisoners' Dilemma," *Journal of Economic Theory* **27**, 245-252.

[7] Lucking-Reiley, D., Bryan, D., Prasa, N., and Reeves, D. (1999): "Pennies from eBay: The Determinants of Price in Online Auctions," mimeo.

[8] Paarsch, H. (1997): "Deriving an Estimate of the Optimal Reserve Price: An Application to British Columbian Timber Sales," *Journal of Econometrics* **78**, 333-357.

[9] Reskick, P., Zeckhauser, R., Friedman, E. and K. Kuwabara. (2000): "Reputation Systems," *Communications of the ACM* **43**, 45-48.

[10] Roth, A. and A. Ockenfels (2000): "Last Minute Bidding and the Rules for Ending Second-Price Auctions: Theory and Evidence from a Natural Experiment on the Internet," mimeo.

[11] Shapiro, C. (1983): "Premiums for High Quality Products as Returns to Reputation," *Quarterly Journal of Economics* **98**, 659-680.

[12] Waehrer, Keith (1995): "A Model of Auction Contracts with Liquidated Damages," *Journal of Economic Theory* **67**, 531-555.

Table 1
Descriptive Statistics

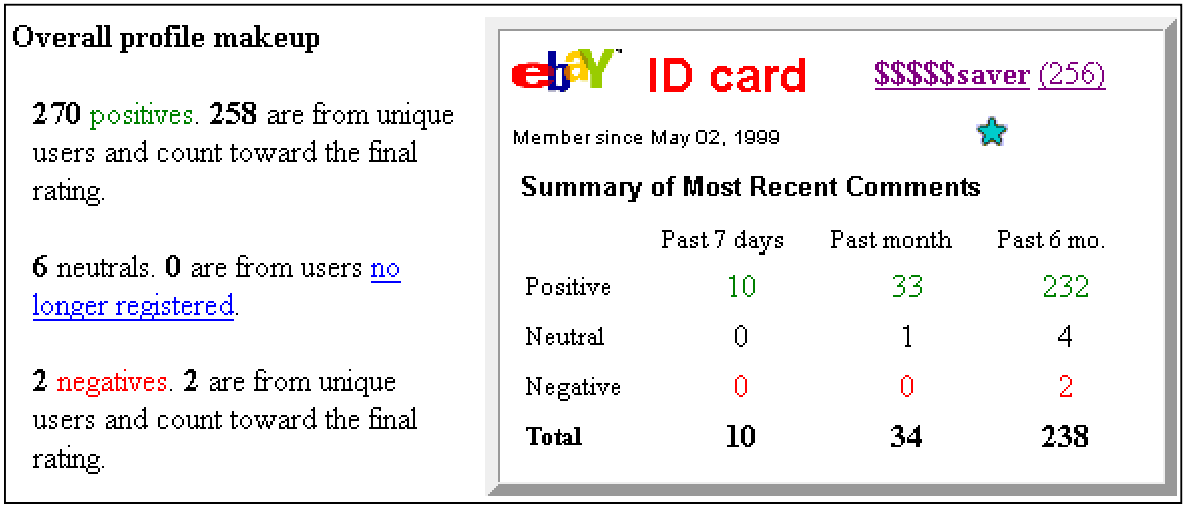
	Variable	Obs	Mean	Std. Dev.	Min	Max
Dependent Variable	**SecondPrice**	94	244.40	19.92	205	303
Reputation Variables	**Shades**	94	0.10	0.30	0	1
	PosReport	94	38.74	118.24	0	1090
	NeutReport	94	0.51	1.59	0	12
	NegReport	94	0.65	2.08	0	12
Auction and Product Characteristic Variables	**Visa**	94	0.09	0.28	0	1
	Used	94	0.11	0.31	0	1
	Retail	94	0.53	0.50	0	1
	Len5	94	0.19	0.40	0	1
	Len7	94	0.33	0.47	0	1
	Len10	94	0.04	0.20	0	1
	Exclude	94	0.13	0.34	0	1
	MarketPrice	94	219.63	5.18	215	229

Table 2
Second Price GLS Results

	Variable	Estimate	Std. Err.
Coefficients	Shades	-0.001	0.025
	LogPosRep	0.017	0.005
	LogNonposRep	-0.024	0.009
	Visa	0.032	0.027
	Used	-0.036	0.023
	Retail	0.047	0.016
	Len5	0.020	0.023
	Len7	-0.007	0.017
	Len10	0.015	0.028
	Exclude	-0.025	0.024
	LogMarketPrice	1.144	0.351
	Constant	-0.719	1.898
Covariance Matrix	σ(Length=3 days)	0.074	
	σ(Length=5 days)	0.069	
	σ(Length=7 days)	0.060	
	σ(Length=10 days)	0.046	

Table 3
Buyer Reputation Effects

	Variable	Coef.	Std. Err.
Coefficients	Shades	0.000	0.026
	LogPosRep	0.019	0.006
	LogNonposRep	-0.026	0.009
	Visa	0.031	0.028
	Used	-0.036	0.023
	Retail	0.047	0.016
	Len5	0.019	0.023
	Len7	-0.005	0.017
	Len10	0.015	0.029
	Exclude	-0.030	0.024
	LogMarketPrice	1.219	0.359
	Constant	-1.121	1.937
	LogBuyerPos	-0.005	0.006
	LogBuyerNonpos	-0.012	0.024
Covariance Matrix	σ(Length=3 days)	0.072	
	σ(Length=5 days)	0.070	
	σ(Length=7 days)	0.060	
	σ(Length=10 days)	0.048	



Overall profile makeup

270 positives. **258** are from unique users and count toward the final rating.

6 neutrals. **0** are from users no longer registered.

2 negatives. **2** are from unique users and count toward the final rating.

ID card $$$$$saver (256)

Member since May 02, 1999

Summary of Most Recent Comments

	Past 7 days	Past month	Past 6 mo.
Positive	10	33	232
Neutral	0	1	4
Negative	0	0	2
Total	**10**	**34**	**238**

Figure 1: A Feedback Profile

User: fishingguy (15) **Date:** 01/23/00, 19:23:11 PST **Item:** 223789313

Praise: Quick shipment, product as described. Professional. Smooth transaction.

User: tlsmith40 (1) **Date:** 12/04/99, 01:09:10 PST **Item:** 197307131

Neutral: Slow shipment, very slow response to e-mail. Otherwise a smooth transaction.

Response: Emailed him day after auction closed, Shiped his case day after got his payment.

User: havic43 (15) **Date:** 10/14/99, 20:18:40 PDT **Item:** 154998549

Complaint: Sold me 4.3 hd as new and was a used drive,looked at add no mention of used

Response: Offered his money back when he said he thought it was new & did not send it back

Figure 2: Examples of Feedback