Reputation in Auctions: Theory, and Evidence from eBay*

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Abstract

We develop simple models of two common types of internet auctions and, 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. The models are developed in an independent private value setting, where buyers and sellers have observable heterogeneous reputations (i.e., propensities to default). We characterize equilibrium in both "high-bid" auctions (typically consumer-to-consumer) where the buyer with the highest (proxy) bid wins, and in "reputation-regarding" auctions (typically business-to-business) where the seller may consider the buyers' reputations. Our main empirical result is that seller (but not buyer) reputation has an economically and statistically significant 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 buyers who are widely dispersed geographically to easily identify auctions of interest; 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. eBay, the leader in online consumer auctions, hosts more than three million auctions daily. Freemarkets, a frontrunner in the rapidly expanding business-to-business auction arena, has conducted auctions with a value in excess of 4 billion dollars since 1995.

With the growth of online markets comes an increasing need for buyers and sellers to engage in transactions with counterparts with whom they have had little or no previous interaction. This introduces risks to traders. 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] In consumer auctions the main risks are that the winner of the auction may not deliver payment, the seller may not deliver the good, or the good delivered may not be as the seller described. In business-to-business procurement auctions (also known as "reverse" auctions) the buyer is concerned, for example, with whether the sellers have the technical expertise to fulfill the contract and whether the sellers are financially stable.

The present paper develops theoretical models of two common types of online auctions – "high bid" auctions (typically consumer-to-consumer) and "reputation regarding" auctions (typically business-to-business) – when traders face the risk that their counterpart may default on the auction contract, and when traders have observable and heterogeneous reputations for default. Our theoretical results suggest a simple procedure to quantify the importance of buyer and seller reputations on auction prices. We use this procedure to examine reputation effects in a data set drawn

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

from eBay.

The Theory

We model auctions in which traders may default on the auction contract, and where each trader evaluates this risk on the basis of his counterpart's reputation. A buyer's reputation is represented by the probability that, if he wins the auction, he will deliver payment. The seller's reputation is 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 buyer is privately informed of his own value.

We begin with a model of typical consumer-to-consumer auctions of a single item. These auctions are conducted as English auctions with "proxy" bidding. Proxy bidding allows a buyer to enter the maximum amount he is willing to bid (although he may revise his proxy bid in the course of the auction). The auction site then bids for the buyer, bidding only enough to outbid other buyers, until either the maximum is reached or the auction ends. When the auction ends the high bidder wins the auction, and so we refer to this type of auction as a "high-bid" auction. We establish the (intuitive) result that the equilibrium proxy bid of the buyer 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 buyers' reputations. This result is the foundation of our empirical analysis of reputation effects. We also define a notion of efficiency and establish that high-bid auctions are inefficient.

In the second auction format we model, a buyer may raise his own bid at any time (he need not bid above the current high bid), and the seller need not select the buyer with the highest bid as the winner, but may also consider the buyers' reputations. We refer to this type of auction as a reputation-regarding auction. We show that the buyer with the highest "reputation-adjusted" value wins the auction and the buyer with the second highest "reputation-adjusted" value bids his expected value of winning the auction. (A buyer's reputation-adjusted value is his value multiplied by the probability he delivers payment.) In equilibrium, the winning buyer's bid is decreasing in his own reputation, but is increasing in the reputation of the buyer with the second highest reputation-adjusted value. We establish that equilibrium in reputation-regarding auctions is efficient.

While we cast both models as consumer-to-consumer auctions of a single item (one seller, many buyers), by symmetry in our results to be reinterpreted in a straightforward way to apply to business-to-business procurement auctions (one buyer, many sellers). Our results for reputation-regarding auctions, for example, can be reinterpreted to apply to the procurement auctions held by Freemarkets in which sellers may lower their bids at any time and the buyer need not accept the lowest bid, but may consider each seller's reputation.

The Evidence

Our theoretical results for high-bid auctions suggest that seller (but not buyer) 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 theory of consumer auctions. We then take the model to a dataset that we construct 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 buyers pay a statistically and economically significant premium to sellers with better reputations. We also examine the effect of buyer reputation on price and find that the effect is statistically insignificant, which is consistent with our theory for high-bid auctions.

Although we think it would be interesting, we do not carry out the same analysis for reputation-regarding auctions. We are not aware of publicly available data on prices and reputation for this type of auction.

To our knowledge our work is the first to model auctions in which buyers and sellers have heterogeneous reputations (i.e., heterogeneous propensities to default). Default in auctions has received only limited theoretical attention in models with ex-ante identical buyers. 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.

Two important studies that are related to the empirical component of our work are the papers by Lucking-Reily et. al. (1999) and Bajari and Hortaçsu (1999). Both of these papers examine collectible coin auctions on eBay. Lucking-Reily et. al. provides some of the first empirical evidence on reputation effects in internet auctions. Bajari and Hortaçsu estimate a structural model of endogenous auction entry, but do not consider reputation effects.

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. Results for high-bid and reputation-regarding auctions are presented in Section 3, along with a discussion of empirical methods. 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 how sellers list items, 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). 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 \$.01, without a reserve, and which sells for \$245 (approximately the mean price in our data), the listing fee would be $.25 and the final value fee would be $6.75.

Bidding

Auctions of a single item are conducted as English ascending bid auctions with "proxy" bidding. As eBay describes proxy bidding, a buyer 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 buyer to enter a bid is Buyer 1 and he enters a proxy bid of $10.00, then Buyer 1 has the high bid, and the high bid is $1.00. (A buyer considering whether to bid only observes the high bid and the user ID's of the buyers 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 Buyer 2 enters a proxy bid of $6.00. Buyer 2 is immediately outbid by eBay which, acting on Buyer 1's behalf, increases his bid to $6.00 plus the minimum bid increment (now $0.50). The new minimum bid is $7.00. If Buyer 3 enters a proxy bid of $15.00, then Buyer 1 is outbid, and Buyer 3 has the high bid of $10.50. If there are no further bids by the time the auction ends, then Buyer 3 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 Buyer 1 bids $10.00, then as before Buyer 1 has the high bid (of $1.00) and the reserve has not been met. If Buyer 2 bids $6.00, then Buyer 1 still has the high bid (now of $6.50) and the reserve is still not met. If Buyer 3 bids $15, then Buyer 3 has the high bid of $12.00, the reserve price, and the reserve is now met.

A buyer 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 buyer to retract his bid. (In a move apparently designed to discourage bid retraction, as of the Spring of 2000 an eBay user's feedback profile also provides the number of times he has retracted a bid in the last 6 months.) At the end of an auction, the seller and the winning buyer exchange email to confirm the outcome of the auction and to discuss arrangements for completing the transaction. Assuming that an escrow service is not used, the buyer pays the seller first and the seller then ships the item.

Default

According to eBay, the auction contract between a seller and the winning buyer 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 buyer.[2] In the spring of 2000 eBay has taken further steps to discourage non-paying bidders. 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. 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.

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

Until the spring of 2000, any eBay user could leave feedback about another user, whether or not they had completed a transaction (except for negative feedback which had to be transaction related). As of the spring of 2000, however, all feedback is transaction related. Some typical positive, neutral, and negative comments are displayed in Figure 2.

Figure 2 goes here.

3 The Model

We model auctions in which traders may default on the auction contract, and where each trader evaluates this risk on the basis of his counterpart's reputation. There is a single seller and n buyers. The seller has a single unit of an indivisible good for auction, with cost normalized to zero. Buyer 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. Buyer i's reputation is described by a probability $r_i^B \in (0, 1]$ that buyer 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 buyers' and sellers' public feedback profiles.

If buyer 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 buyer is zero. Here we have not modeled the buyer's decision to default, but it is straightforward to do so.[3]

[3]Rational buyer default can be modelled as follows: Assume that buyer 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 buyer i is privately informed of v_i. Each buyer i's

High-bid and reputation regarding auctions are dynamic games of incomplete information. Since only the buyers' 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.

High-bid auctions

We first consider an auction format which is a stylized representation of consumer-to-consumer auctions, such as single-unit auctions on eBay. In the auction, buyers choose "proxy" bids. If $(b_1, \ldots, b_n)$ is a profile of proxy bids, then we say that **buyer** i **has the high bid** if $b_i \geq b_j \ \forall j \neq i$, i.e., if buyer i has the highest proxy bid. If buyer 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 buyer observes only the amount of the high bid. To change his proxy bid, a buyer's new bid must be greater than the current high bid. We assume that a buyer who does not have the high bid is always able to increase his bid before the auction ends.[4] The buyer who has the high bid when the auction ends wins the auction, and he pays the high bid. We refer to this auction format as a "high-bid" auction, since the buyer with the high-bid wins the auction.

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

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

Consider a buyer $j \neq i$ who would not win if bidding terminated. For buyer j to

reputation r_i^B, and hence each distribution X_i, is commonly known.) Before making payment, but after the auction terminates, buyer i privately observes x_i, the realized value of X_i. If buyer 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 buyer 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.

[4]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 buyer who did not win the auction generally did have time to revise his bid.

change his proxy bid, his new bid must exceed the high bid, i.e., his new bid $\hat{b}_j$ must satisfy $\hat{b}_j > \max_{k \neq i} b_k$. Bidding will terminate only if, for each non-winning buyer j, even the smallest such bid is more than buyer 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 buyer will ever bid above his value.

Combining conditions (1)-(3), we obtain a definition of equilibrium in a high-bid auction.

Definition: An equilibrium of the high-bid auction is a pair $\{(b_1^*, \ldots, b_n^*), i^*\}$, where $(b_1^* \ldots, b_n^*)$ is a profile of bids and buyer i^* is the winning buyer, 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 high-bid auction (i) the buyer with the highest value wins the auction, and (ii) he pays the expected value of winning the auction for the buyer with the second highest value. It also establishes that it is an equilibrium for every buyer 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 buyers have the same value, and relabel the buyers so that $v_1 > v_2 > \ldots > v_n$.

Proposition 1: If $\{(b_1^*, \ldots, b_n^*), i^*\}$ is an equilibrium of the high-bid auction, 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 of the high-bid auction, where $b_j^* = r^S v_j \ \forall j$.

The proposition allows that buyers (other than the buyer 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 buyer is able to revise his proxy bid, subsequent bids by other buyers may raise the high bid above his expected value of winning the auction. In this case, the buyer's last proxy bid (which is the bid observed in eBay bid histories) may be less than his expected value of winning.

Reputation-Regarding Auctions

We next consider an auction format which is a stylized model of business-to-business auctions like Freemarkets'. The rules of the auction are as follows: All bids are observable. When the auction opens each buyer has a bid of zero. A buyer may raise his bid at any time before the auction terminates by an arbitrary (positive) amount. In particular, a buyer's new bid need not exceed the maximum of all the other buyers' bids. Once bidding terminates, the seller selects the winning buyer, who then pays his own bid (if he does not default). If the seller selects buyer i as the winner and buyer i has bid b, then the seller's expected payoff is $r_i^B b$. (The seller's expected payoff ignores the possibility that the seller approaches the second highest bidder if the winner of the auction defaults, since in the meantime the buyer may have purchased the item elsewhere.) The seller need not select the buyer with the highest bid as the winner, but may also consider the bidders' reputations. Hence, we refer to this auction format as reputation-regarding auction.

We now identify the conditions that a terminal profile of bids must satisfy. Suppose $(b_1, \ldots, b_n)$ is a profile of bids. If there are no further bids, then the winner of the auction is the buyer i whose bid is most valuable to the seller, i.e., the buyer for whom

$$r_i^B b_i = \max_k r_k^B b_k. \tag{4}$$

We suppose that when buyer i made his current bid b_i, he made the smallest bid for which the seller (weakly) prefers his bid to the bids of all the remaining buyers, i.e., he chose b_i so that[5]

$$r_i^B b_i = r_j^B b_j \text{ for some } j. \tag{5}$$

[5] We could require buyer i's bid be the smallest bid the seller *strictly* prefers. That would require introducing a smallest bid increment which, for simplicity, we avoid here.

Consider a non-winning buyer j. A bid of $\hat{b}_j$ by buyer j is preferred by the seller to buyer i's bid only if $r_j^B \hat{b}_j \geq r_i^B b_i$. Bidding will terminate only if, for each non-winning buyer j, even the smallest such bid (i.e., a bid of $\hat{b}_j = r_i^B b_i / r_j^B$) is more than buyer j's expected value of winning the auction, i.e.,

$$r^S v_j \leq \frac{r_i^B}{r_j^B} b_i \;\forall j \neq i. \tag{6}$$

Finally, when bidding terminates, no buyer will have bid above his expected value of winning the auction, i.e.,

$$b_j \leq r^S v_j \;\forall j. \tag{7}$$

Combining conditions (4)-(7), we obtain a definition of equilibrium in reputation-regarding auctions.

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

$$\begin{array}{llcll} \text{(i)} & r_{i^*}^B b_{i^*}^* & = & \max_k r_k^B b_k^*. & \\ & r_{i^*}^B b_{i^*}^* & = & r_j^B b_j^* & \text{for some } j \neq i^*. \\ \text{(ii)} & r^S v_j & \leq & \frac{r_{i^*}^B}{r_j^B} b_{i^*}^* & \forall\, j \neq i^*. \\ \text{(iii)} & b_j^* & \leq & r^S v_j & \forall j. \end{array}$$

Define $r_i^B v_i$ to be the **reputation-adjusted value of buyer** i. It is the expected value to the seller of a bid by buyer i of v_i. To simplify the statement of our results we ignore ties, and relabel buyers so that $r_1^B v_1 > r_2^B v_2 > \ldots > r_n^B v_n$.

Proposition 2, which follows, establishes that the winner of the reputation-regarding auction is the buyer with the highest reputation-adjusted value. The buyer with the second highest reputation-adjusted value bids his expected value of winning the auction. The seller is indifferent between the bids of the buyer with the highest and the buyer with the second highest reputation adjusted values. Hence, the winning buyer pays a premium (discount) if his reputation is lower (higher) than the reputation of the buyer with the second highest reputation-adjusted value.

Proposition 2: If $\{(b_1^*, \ldots, b_n^*), i^*\}$ is an equilibrium of the reputation-regarding auction, then $i^* = 1$,

$$b_1^* = \frac{r_2^B}{r_1^B} b_2^*, \text{ and } b_2^* = r^S v_2.$$

Proposition 3: An equilibrium in the reputation-regarding auction exists. In particular, $\{(b_1^*, \ldots, b_n^*), 1\}$ is an equilibrium, where

$$b_1^* = \frac{r_2^B}{r_1^B} b_2^*,$$

and $b_j^* = r_j^B v_j$ for $j > 1$.

Clearly if all buyers have the same reputation, then the auction outcome is the same in the high-bid auction and the reputation-regarding auction. This result is formalized in Corollary 1.

Corollary 1: Suppose that $r_1^B = \ldots = r_n^B$. If $\{(b_1^*, \ldots, b_n^*), i^*\}$ is an equilibrium of the high-bid auction and $\{(b_1', \ldots, b_n'), i'\}$ is an equilibrium of the reputation-regarding auction, then Buyer 1 wins in both auctions and he pays $r^S v_2$, i.e., $i^* = i' = 1$ and $\max_{k>1} b_k^* = b_1' = r^S v_2$.

Auction Efficiency

If buyer i wins the auction, then the sum of his payoff and the seller's payoff is $r^S r_i^B v_i$. We say that the auction is **efficient** if the item is allocated to the buyer for whom $r^S r_i^B v_i$ is maximized.

It is immediate from Proposition 2 that the reputation-regarding auction is efficient. In contrast, equilibrium in the high-bid auction is generally not efficient. Suppose that there are two buyers with values v_1 and v_2, with $v_1 > v_2$ but with $r_1^B v_1 < r_2^B v_2$. Then buyer 1 wins the high-bid auction and the allocation is inefficient. The source of the inefficiency is that the high-bid auction does not allow the seller to make trade-offs between the price and the reputation of the buyer – the highest bid wins.[6]

[6] On eBay, sellers may instruct low-reputation buyers not to bid and, before the auction terminates, may cancel the bids of buyers whose reputation is unacceptable. This may enhance efficiency.

Empirical Method

Our results for high-bid auctions provide a simple framework within which to quantify the effect of reputation on price. This framework is not structural in the sense that we do not make an effort to fully characterize the density of buyers' values. Instead, our procedure is more closely related to that of Hendricks and Porter (1988) who develop and impose the restrictions of a theory in their empirical work but make no effort to derive structural estimates.[7]

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

$$\log(b^*_{i2}) = \log(r_i^S) + \log(v_{i2}). \tag{8}$$

Our interest is in implementing (8) 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 buyers evaluate seller i's reputation according to the following:

$$r_i^S = \lambda x_{i1}^{\theta_1} x_{i2}^{\theta_2} \cdots x_{iK}^{\theta_K}, \tag{9}$$

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:

$$v_{i2} = \phi y_{i1}^{\pi_1} y_{i2}^{\pi_2} \cdots y_{iM}^{\pi_M} e^{\eta_{i2}}, \tag{10}$$

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 buyer with the second highest bid in auction i. Note that differences in bids in auction i are due entirely to

[7] Good surveys of structural and nonstructural empirical work in auctions are available in Hendricks and Paarsch (1995) and Donald and Paarsch (1996).

different realizations of the buyers' idiosyncratic value draws. As a result, the buyer 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 buyers in the auction.[8] We assume that the idiosyncratic value draws are i.i.d., and that the number of buyers 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 (8) 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 (9) and (10), we obtain the following empirical model of auction i's second highest bid:

$$\begin{aligned} \log(b^*_{i2}) &= c + \widetilde{x}'_i\theta + \widetilde{y}'_i\pi + \alpha_{t_i} + \varepsilon_{i2}, \\ E(\varepsilon_{i2}) &= 0,\ Var(\varepsilon_{i2}) = \sigma^2_{t_i}, \end{aligned} \tag{11}$$

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 (11) 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 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,

[8] The number of buyers may be greater than the number of observed bidders since a buyer will not bid if their value for the item is less than the high bid when they first view the auction.

consistent and asymptotically efficient estimates for the parameters of the system can be obtained through generalized least squares procedures.[9]

4 Evidence from eBay

Our empirical analysis is based on auctions for 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 has more than 70% of the consumer-to-consumer auction market.

Processor auctions provide an excellent environment to study reputation effects for a number of reasons. First, PIII 500's processors are essentially homogeneous. Hence, the price variation observed in auctions can be traced to variation in the trader's reputations, and to random variation in buyer values, and not to variation in the good being auctioned. 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 buyer. It 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 collectable coins, say) processor prices tend to fall over the long term. Buyers 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 was 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.[10]

While the PIII 500's in our study are physically homogeneous, a processor in

[9] 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-Reily et. al. (1999).

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

March 1999 (when the PIII 500 was introduced) is not the same as a PIII 500 in September 1999 (when we began collecting our data) – in particular, the processors are time-differentiated. Indeed, at the time of its introduction, the processor listed for around $700, but by September 1999 it was no longer a cutting-edge processor, and it was available from retailers for around $240. Further variation in the product is introduced since PIII 500's are available in two types of packages: 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. In contrast, 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.

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 buyer, 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 buyer 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.[11]

The main and bid history pages provide us with most of the data that we need for our empirical analysis. But, for two reasons, they do not provide the information

[11] 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.

we need about reputation. First, these pages only report a user's overall feedback score. To obtain a more precise 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. This is 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.[12] 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 buyer's value in an auction for a processor will be depend on the processor's retail prices. We obtained our data from CPUReview.com which provides, bi-monthly, the lowest advertised 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.

[12] We include shipping costs since we define the item as a Pentium III 500 delivered to the buyer.

Visa takes the value one if the seller accepts payment by credit card. It is included since a buyer'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.[13] 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 buyers, and zero otherwise. We classify a seller as an excluder if the main auction page contained a statement that bids from low-reputation buyers would be cancelled or if he was observed to cancel a bid from a low-reputation buyer. 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 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

[13] In 8 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 buyers 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.

low-reputation buyers. 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 negatives comments left for buyers 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 (11). 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 buyers 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 a retail chip sells for about 5% more than a non-retail chip, a premium that is likely being paid for the extended warranty this product provides. Sellers who excluded buyers 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 suggests that longer auctions do, in fact, attract more buyers, but that this primarily has the effect of reducing the variability of the sale price.

Buyer Reputations

Our model of high-bid auctions predicts that the second highest bid should not depend upon the buyer's own reputation. A simple way to test this prediction is to augment our empirical model with buyer reputation covariates in order to examine their explanatory power.[14] To do this, we define buyer reputation variables exactly analogously to the seller reputation variables: BuyerPos is the log of one plus the number of unique positive comments and BuyerNonPos 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 buyer reputation variables are individually statistically insignificant. A χ^2-test of the null hypothesis that they are

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

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 for high-bid auctions, we find no apparent evidence of buyer reputation effects on the second highest bid for the processors in our data set.[15]

6 Conclusion

The present research models bidding behavior in high-bid and reputation-regarding auctions when traders have heterogenous reputations for default. Our results for high-bid auctions 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 a seller reputation (but not buyer 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. A seller who provides good service can look forward to positive feedback from the buyer 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 buyer who routinely delivers payment 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 performance. For example, do sellers with more positive feedback perform better in future transactions than sellers with less positive feedback? Our finding that buyers pay more to sellers with better reputations suggests that buyers believe this is the case.

[15] In eBay auctions, to complete a transaction, the buyer first sends payment and the seller then delivers the item. Hence, the cost to sellers of nonpayment is relatively small, and for this reason one might also expect buyer reputation not to be economically significant.

In principle, 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 of the high-bid auction 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 $\max_{k \neq 1} b_k^* < r^S v_2$. Hence $r^S v_2 - \max_{k \neq 1} b_k^* > 0$, 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 of the high bid auction. 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 $r^S v_j - \max_{k \neq 1} b_k^* \leq 0 \ \forall j > 1$. Condition (iii) in the definition of equilibrium is satisfied by construction. ¤

Proof of Proposition 2: Let $\{(b_1^*, \ldots, b_n^*), i^*\}$ be an equilibrium of the reputation-regarding auction and suppose that $i^* > 1$. Then

$$\begin{aligned} r^S v_1 - \frac{r_{i^*}^B}{r_1^B} b_{i^*} &\geq r^S v_1 - \frac{r_{i^*}^B}{r_1^B} r^S v_{i^*} && \text{by (iii)} \\ &= \frac{r^S}{r_1^B}(r_1^B v_1 - r_{i^*}^B v_{i^*}) \\ &> 0 && \text{since } r_1^B v_1 > \ldots > r_n^B v_n, \end{aligned}$$

which contradicts (ii), for $j = 1$, in the definition of equilibrium. Hence $i^* = 1$.

Next, we establish that $b_1^* = \frac{r_2^B}{r_1^B} b_2^*$, i.e., $r_1^B b_1^* = r_2^B b_2^*$. Since $i^* = 1$, by (i) we have that $r_1^B b_1^* = r_j^B b_j^*$ for some $j > 1$. Suppose $r_1^B b_1^* = r_k^B b_k^*$ for $k > 2$. Then

$$\begin{aligned} r^S v_2 - \frac{r_1^B}{r_2^B} b_1^* &= r^S v_2 - \frac{r_k^B}{r_2^B} b_k^* && \text{since } r_1^B b_1^* = r_k^B b_k^* \\ &\geq r^S v_2 - \frac{r_k^B}{r_2^B} r^S v_k && \text{by (iii)} \\ &= \frac{r^S}{r_2^B} (r_2^B v_2 - r_k^B v_k) && \text{by (iii).} \\ &> 0 && \text{since } r_2^B v_2 > \ldots > r_n^B v_n. \end{aligned}$$

Hence $r^S v_2 > \frac{r_1^B}{r_2^B} b_1^*$, which contradicts (ii) for $j = 2$. Thus $r_1^B b_1^* = r_2^B b_2^*$.

We now show that $b_2^* = r^S v_2$. By (iii) we know that $b_2^* \leq r^S v_2$. Suppose that $b_2^* < r^S v_2$. Then

$$\begin{aligned} r^S v_2 - \frac{r_1^B}{r_2^B} b_1^* &= r^S v_2 - \frac{r_1^B}{r_2^B} \left(\frac{r_2^B}{r_1^B} b_2^* \right) && \text{since } r_1^B b_1^* = r_2^B b_2^* \\ &= r^S v_2 - b_2^* \\ &> 0 && \text{since } b_2^* < r^S v_2. \end{aligned}$$

Hence $r^S v_2 > \frac{r_1^B}{r_2^B} b_1^*$, which contradicts (ii) for $j = 2$. ¤

Proof of Proposition 3: We need to check that conditions (i)-(iii) of the definition of equilibrium are satisfied. We have for each $j > 1$ that

$$r_1^B b_1^* = r^S r_2^B v_2 \geq r^S r_j^B v_j,$$

where the equality follow from the definition of b_1^* and where the inequality follows from $r_2^B v_2 > \ldots > r_n^B v_n$. Hence (i) holds. To see condition (ii) holds, notice that for each $j > 1$

$$r^S v_j - \frac{r_1^B}{r_j^B} b_1^* = r^S v_j - \frac{r_1^B}{r_j^B} \left(r^S \frac{r_2^B v_2}{r_1^B} \right) = \frac{r^S}{r_j^B} (r_j^B v_j - r_2^B v_2) \leq 0,$$

where the inequality since $r_2^B v_2 > \ldots > r_n^B v_n$. Clearly $b_1^* = r^S r_2^B v_2 / r_1^B < r^S v_1$. For $j > 1$, we have $b_2^* = r_j^B v_j$. Hence (iii) holds. ¤

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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	

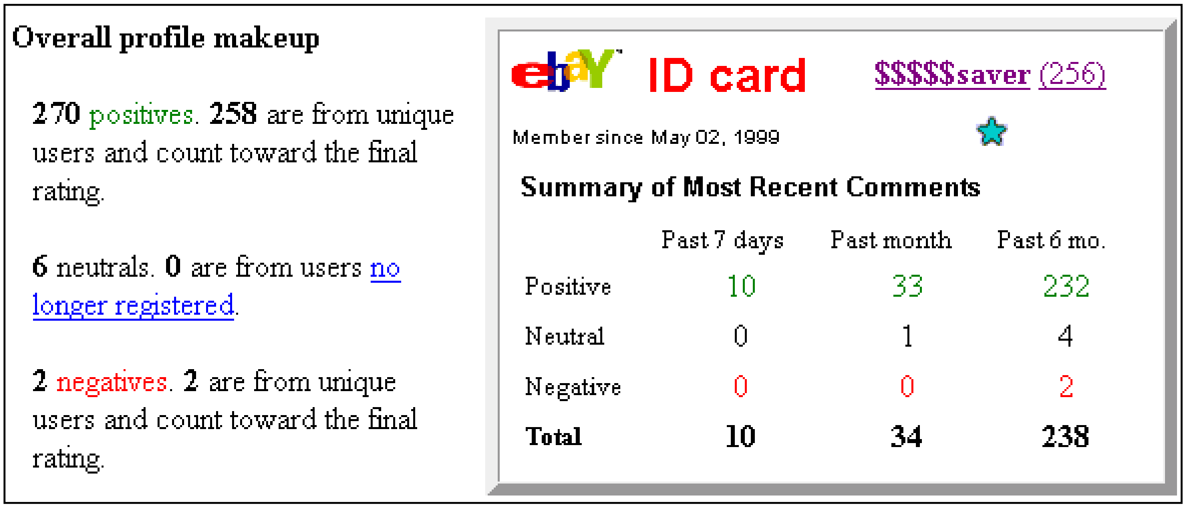

Figure 1: A Feedback Profile

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