December 2004

Trust-building on the Internet: evidence from eBay

Jie Zhang
University of Toledo

Trust-building on the Internet: evidence from eBay

Jie Zhang
College of Business Administration
University of Toledo
Jennifer.zhang@utoledo.edu

Abstract

Online auction web sites provide a convenient yet risky trading venue for the participants. The uncertainty about the product quality and the credibility of the traders, however, may impede the liquidity and efficiency of the trades in online auctions. This research seeks to establish a framework to better assess the effect of a seller's feedback "reputation" on the closing price of an online auction. In contrast to the literature on reputation in Internet auction, we claim and prove that buyers assess a seller's reputation from her feedbacks related to her selling activities only but not those from both sales and purchases. We build a model to illustrate how this reputation system works and test the hypotheses with data collected from the eBay web site on auctions of Apple iPod MP3 players. It is found that (1) the numbers of a seller's positive and negative comments from her buyers solely are significantly correlated with the bidding price of her sales transactions; (2) the numbers of a seller's positive or negative comments earned in her purchasing transactions are not significant in explaining the bidding price of her sales transactions; (3) negative comments are weighted more heavily than positive ones.

Key Words: Online auction, Reputation, Trust

1. Introduction

Electronic business has grown dramatically over the past decade, represented by more than 25 percent growth rate in annual sales (US Census Bureau). Consumer-to-consumer online auction web sites, for example, eBay.com, Yahoo! Auction, and Amazon auction etc., have become one of the most successful business models of electronic commerce. With 9.4 million registered users, 971 million items listed, and $24 billion worth of items sold in 2003, eBay has become the fastest growing and the most popular online auction market among the all. It realized $2.17 billion net revenue in 2003, a 78 percent increase over the year before. In addition, eBay has expanded its operation scope into 28 foreign countries other than the US. The fast growing revenue from online auction business has shown a promising future of the e-commerce.

The success of the auction web sites comes from several advantages: (1) The Internet provides convenient and efficient marketplace for the consumers to trade among each other. In contrast with the auction in a physical auction site, online auction provides anonymity, accuracy, and interactiveness to the customers so that the transactions become more transparent and up-to-date. (2) More importantly, online auction has very low entry cost for the sellers. Any ordinary individual can easily bring her goods to millions of potentially interested buyers worldwide without setting up any storefronts or bearing with the high cost incurred in transactions. Online auction web sites offer a virtual “flea market” where everyone can become a seller as easily as being a buyer.

However, the ideal “frictionless” marketplace cannot exist without building trust among online traders. Traders exist in the name of their user IDs, which could be created and changed easily. A trader could possibly have as many identities on the Internet as have “eyebrows” in the real life. The anonymity and virtuality of the traders’ online identity challenges trust building on the Internet community, especially in the consumer-to-consumer online auction web sites. It is difficult for the traders to tell the difference between reputable online sellers and criminals who use the Internet to rob people. Online auctions remain the number one aching for Internet fraud. According to the Internet Fraud Watch operated by the National Consumers League, online auction frauds accounted for 90 percent of the total frauds reported to the Internet Fraud Watch in 2002 and the average loss per person rose from $310 in 1999 to around $468 in 2002, indicating the deterioration in online trading safety.

To mitigate the negative effect of frauds happened in online auction, many auction web sites have set up some feedback forums with comments about the sellers based on other people’s experiences (Figure 1). The basic idea is to use the inputs from the traders about their own experiences of trading with that user ID to signal all the other traders about that traders’ credibility and affect their behavior accordingly. Those feedback mechanisms are expected to reflect the true reputation of the traders and to help identifying the fraudulent ones. Moreover, the downside effect of getting negative ratings is also expected to threaten the participants to behave well in the transactions involved on those web sites.

A serial of research took the data from eBay transactions and examined the effect of online feedback profiles on bidding outcomes: Ba and Pavlou 2002, Bajari and Hortacsu 2003, Houser and Wooders 2000, Melnik and Alm 2002, McDonald and Slawson 2002, to name a few. As shown in Section 2 of the paper, fruitful results have been achieved in the literature.

But in our view, one of the most important feature of online auction markets, or more generally, most e-commerce markets, is these new markets greatly reduce transaction cost, particularly, there is very low entry cost for sellers. This means sellers are no longer sellers in the traditional sense, usually a firm, or a retailer store, which sells large quantity of product to the market with almost no purchase from the market. Now any user can sell there goods in the market with a very low fee. A user can be a buyer for some time, and a seller for other times. Actually, this is the defining feature, and the basic idea behind eBay - the billion-dollar business - a “flea market”. Unfortunately, the important implication of this feature has almost been completely ignored in the literature. All the paper mentioned above assume sellers only sell in the markets, while buyers only purchase from the markets.

Our paper is the first attempt to investigate the importance of such a feature. Specifically, we show that since any user can always change her role at any time in these online auction markets, which they do, any user’s reputation actually has two components: her “selling reputation”, coming from her previous selling records and her “buying reputation”, coming from her previous buying records. And given the current mechanism design of these markets, the costs and benefits to build the two reputations are different for users. This gives incentive for users to strategically manipulate their reputations. But rational buyers should be able to understand this and would separate a seller's selling reputation from buying reputation when trying to infer the true probability of receiving the product. As a result, the two types of reputation have very different effects on winning prices. In our model, with the assumption that sellers only ship the product when payments are received, we show that sellers' good selling reputation increase winning prices, bad selling reputation reduce winning prices, while sellers' buying reputation has no significant effect on winning prices.

Using actual auction data collected from eBay, we show empirically that first, sellers do make purchases as well as sales, in our sample, for an average seller, 38 percent of all the transactions are actually purchases, and for some sellers, it can be as high as 99 percent. 39 percent of the sellers have buying transaction more that 50 percent; second, the effects of the two types of reputation confirm our theoretical prediction. Sellers' good selling feedback increases sell prices, bad selling feedback reduces sell prices, and sellers' buying feedback have the wrong signs and are not statistically significant. We do find some other variables, such as product condition and accepted payment methods, also affect the sell prices.

Hence our paper contributes to the literature by clarifying the meaning of reputation in online auction markets theoretically and empirically. This may change some of the previous results obtained in the literature, for example, some papers find no significant effect of positive and/or negative reputations, and this is possibly due to the inclusion of sellers' "buying feedback" dampen the effect of reputation. More importantly, our results call for more attention to the strategic aspects of reputation and rethinking of the long-short run player reputation framework frequently used in the literature.

The paper is organized as follows. Section 2 briefly reviews the literature on theoretical conclusions on reputation and empirical results on the effect online feedback profiles. A model pointing out our idea is brought out in Section 3. Then Section 4 shows the empirical evidence and tests hypotheses. Section 5 summaries the whole work and discusses the limitation and opportunities for further research.

2. Literature Review

The reputation formation and has been extensively studied in economics using game theory. The reputation literature, for example, Kreps and Wilson 1982, Milgrom and Roberts 1982, Fudenberg and Levine 1992, Klein and Leffler 1981, Cripps, Mailath and Samuelson 2002, suggests that the feedback mechanisms used in the online auction web sites can enforce the traders to take the cooperation strategy and act honestly.[1]

A review of principal empirical research results on online feedback forums is shown in Table 1.[2] They mainly studied the impact of feedback ratings on the prices and probability of sales. A trader can observe any other trader's feedback comments left by her trading partners in the previous transactions. Actions of either a buyer or a seller, such as willingness to bid, bidding prices setting, determination to complete the transactions, will be influenced by the ratings of her trading partners.

Table 1 Summary of Principal Research Literature

Citation	**Items sold**	**Remarks**
Ba and Pavlou, 2002	Music, software, Electronics	Positive feedback increased estimated price, but negative feedback did not have an effect
Bajari and Hortacsu, 2003	Coins	Both positive and negative feedback affect probability of modeled buyer entry into the auction, but only positive

[1] For a detailed review, see Dellarocas 2003.
[2] Adapted from Resnick Zeckhauser, Swanson and Lockwood, 2002.

		feedback had a significant effect on final price
Dewan and Hsu, 2001	Stamps	Higher net score increases price
Eaton, 2002	Electric guitars	Negative feedback reduces probability of sale, but not price of sold items
Houser and Wooders, 2000	Pentium chips	Positive feedback increases price; negative feedback reduces it
Kalyanam and McIntyre, 2001	Palm Pilot PDAs	Positive feedback increases price; negative feedback reduces price
Kauffman and Wood, 2000	Coins	No significant effects, but negative feedback seems to increase price (!) in univariate analysis
Lee, Im and Lee, 2000	Computer monitors and printers	Negative feedback reduces price, but only for used items
Livingston	Golf clubs	Positive feedback increases both likelihood of sale and price; effect tapers off once a record is established
Lucking-Reiley et al., 2000	Coins	No effect from positive feedback; negative feedback reduces price
Melnik and Alm, 2002	Gold coins	Positive feedback increases price; negative feedback decreases price
McDonald and Slawson, 2002	Dolls	Higher net score (positives -negatives) increases price
Resnick and Zeckhauser, 2002	MP3 players, Beanie babies	Both forms of feedback affect probability of sale but not price contingent on sale
Resnick Zeckhauser, Swanson and Lockwood, 2002	Vintage postcards	Controlled field experiment; established seller commands higher prices than newcomers; among newcomers, small amounts of negative feedback have little effect

However, they made assumption based on the traditional reputation theory that a customer is either good or bad and that characteristics never change over time. Their findings of the relationship between the seller's reputation and the bidding price are ambiguous. When I assume strategic customers, they may behave differently from what the literature presented. For example, they can manipulate the values of their ratings by acting differently as a buyer from as a seller, or across different transaction amounts. In this case, the ratings do not correlated directly with the total value of ratings, but the buyers would care about the positive ratings of the customers as a seller exclusively, and vice versa. I expect that the empirical test under this assumption can lead to better results and can explain the mixed results obtained in the previous studies. None of the literature has separated the comments of a seller earned from her sellers from those from her buyers.

If the above hypotheses are proved, more suggestions can be provided to the online auction companies to improve their feedback mechanism, such as separating the ratings as a buyer or as a seller, give a weight to the scores of the ratings, etc.[3]

The phenomenon that some sellers do not solely sell, but also buy on eBay has been noticed in the literature, for example, Cabral and Hortacsu [2003] found in their dataset, that 38 percent of the sellers in the Beanie baby and silver proof set, 33 percent in gold coins, and 20 percent in ThinkPad categories followed the "buy first, sell later" strategy. So they conclude that "buy first and sell later" is a widespread phenomenon on eBay and they interpret this as evidence that some sellers start off by investing (as a buyer) on an initial

[3] While we were working on this paper in January 2004, eBay changed its display of member feedback profiles by separating their feedback from buyers from those from sellers, exactly as we have suggested.

reputation history, assuming that buyers would take the initial record of sellers as a genuine selling record although it contains selling as well as buying. Unsurprisingly, their empirical test didn't support their theoretical prediction that sellers with bad reputation should engage in this activity.

Essentially, we are asking what the effect of a seller's buying record on her reputation as a seller, or on the auction price are. So we are not limiting our attention to this particular "buy first, sell later" phenomenon. If a seller's buying records are generally good, and if the good purchasing records did improve the seller's "reputation" as a buyer, and increase her selling prices, there is nothing preventing the seller from buying the good reputation at any time after her initial period on eBay, though she may be more eager to do so at the beginning. But if buyers are capable of distinguishing a seller's selling behavior from her buying records, these buying transactions would not affect the seller's "selling reputation", hence would not affect the auction price. The "buy first and sell later" strategy might just be the result of a natural fact that people begin to deal with eBay and learn the rules from their purchasing transactions, and only start to sell when they get more experienced and interested later on. Any other purchase after the initial period could also arise from true demand of the products, instead of strategic manipulation of reputation.

3. The Model

A fully developed model would be very complicate because now there are no short lived buyers. All users are long run player and have to solve dynamic maximization problem in order to make decision of selling, buying, or how much to bid. Specifically, since bidders have to contempt the effect of her bid behavior on her reputation, and hence long run profit, we lose the ability to use the elegant long-run/short-run player reputation framework developed since Klein and Leffler [1981], Sharpiro [1983], and applied to ecommerce setting by Dellacoce [2002]. Sine we only want to demonstrate that the reputation of the player when they are playing different roles have different meaning for other players, we assume for now that the bidding decision is static, and leave strategic buying/bidding of sellers for further research. We will show this condition is satisfied in the equilibrium.

We develop a simple model based on Houser and Wooders [2000] to illustrate our point. Assume all players live infinite periods. A player, or a user, can sell a unit of indivisible product, or purchase a unit in any period. We assume whether to buy, or sell in current period is determined exogenously.

There are two types of players, H (honest) and D (dishonest), and the fraction of honest player is $\theta \in [0,1]$, which is common knowledge to all players. But the exact type of a player is private information of that player.

If a user sells a unit of the product in current period, she becomes a seller. She lists the product on eBay, provides description of the product, shipping, payment and other information, and perhaps picture of the product.

Other users who want to buy the product then submit bid for the product. Buyer i's value of the good is v_i, which is randomly drawn from a continuous distribution $V[\underline{v}, \bar{v}]$. The auction is a sealed second price bid. The highest bidder wins the auction, and pays the price of the second highest bid. After the auction, buyer then can choose to default, or to make payment to the seller.

We assume seller always wait till receive the payment before taking any action. So seller would never ship the product before she actually received payment. This make sure there is no gain from winning a bid but not making payment, so buyers always make payment after win an auction, no matter what type the buyer is.

After receiving payment, a seller can choose to cooperate (co, deliver the goods) or cheat (ch, not deliver the good). An honest player always deliver the good when she is a seller and receive payment from a winning bidder, while a dishonest player does not deliver the goods after receiving payment so she can make immediate profit.

After received the product, or not received the product for long enough time, the buyer report the result to the system and everybody can view the feedback. In addition to any comment, the buyer explicitly gives +1(positive) to a satisfied transaction, -1 to unsatisfied transaction, and 0 (neutral) otherwise. We assume the feedback is noisy. So there is a probability α that the buyer will report a negative feedback even the seller cooperate, and a probability β that the buyer report a positive feedback even the seller cheat.

We assume there is no withdraw of feedback after it is reported.

Given buyer *i*'s value of the good is v_i, the bid function is

$$b(v_i, P_s, N_s, P_b, N_b) = p(P_s, N_s, P_b, N_b)v_i \ , \tag{1}$$

in which $p(P_s, N_s, P_b, N_b)$ is the probability that the seller, with history (P_s, N_s, P_b, N_b), would deliver the goods. P_s, N_s, P_b, N_b are the number of positive, negative feedbacks of the user as seller and buyer, respectively.

Assume the prior consumer belief of θ is p_1, we have following proposition:

Propositon1. If a buyer distinguishes the seller's "selling reputation" and "buying reputation", the posterior expected consumer beliefs of p is given by:

$$(p \mid P_s, N_s, P_b, N_b) = \frac{\alpha^{P_s}(1-\alpha)^{N_s} p_1}{\alpha^{P_s}(1-\alpha)^{N_s} p_1 + \beta^{P_s}(1-\beta)^{N_s}(1-p_1)}; \tag{2}$$

If a buyer takes all feedbacks as the sellers "selling records", as commonly used in the literature, then the posterior expected consumer beliefs of p is given by:

$$\begin{aligned} (p \mid P, N) &= \frac{\alpha^{P}(1-\alpha)^{N} p_1}{\alpha^{P}(1-\alpha)^{N} p_1 + \beta^{P}(1-\beta)^{N}(1-p_1)} \\ &= \frac{\alpha^{P_s+P_b}(1-\alpha)^{N_s+N_b} p_1}{\alpha^{P_s+P_b}(1-\alpha)^{N_s+N_b} p_1 + \beta^{P_s+P_b}(1-\beta)^{N_s+N_b}(1-p_1)} \end{aligned} . \tag{3}$$

Proposition 2: If a buyer distinguishes the seller's "selling reputation" and "buying reputation", bid price will increase with P_s, and decrease with N_s, but will be unrelated with the buying reputation P_b and N_b. If a buyer takes all feedbacks as the sellers "selling records", bid price will increase with P_s and P_b, and decrease with N_s and N_b.

If a buyer does not distinguish the seller's "selling reputation" and "buying reputation", there would be extra incentive for the buyer who wants to improve reputation to bid price higher than the expected value. If such a buyer wins the auction, the price would also reflect her "reputation motives", that is, it is correlated with buyer's reputation. For example, we would expect a buyer with lower reputation would bid higher price. But if buyers can distinguish seller's "selling reputation" and "buying reputation", there is no "reputation motives", and buyers' biding function would again be static.

4. Evidence from eBay

The last step is to use the transaction data to test the hypotheses from the model and from other observations. Observations from the on-line auction website eBay.com were collected in February 2004.

4.1 Data Collection Procedure

We wrote an intelligent web agent (spider) program to collect transaction data and feedback data from eBay's website. First we searched eBay (using search tool they provided on their web site) for auctions containing the keywords "iPod" and check the "completed auction only" checkbox. This took us to a page listing auctions completed within the past two weeks containing the keyword. The spider program will then follow the link to each of the auction pages on the search page and automatically download the relevant transaction data, for example, include trading item, the user ID of the seller and the winning buyer, starting and end date/time of the auction, starting bid prices, end prices, number of bidders participated, description of the auction items etc. The program then goes to the seller's feedback page to download the whole history of the feedbacks the seller has received from her previous transactions. The seller's reputation is measured by such indices as unique number of positive/negative feedback, unique positive/negative feedback ratio. We separate the indices into three groups---from unique sellers, from unique buyers and from both---according to the types of the transaction for that user. The reputation scores are derived from the feedback history up to the end time of the auction, that is, by the exact time the auction is closed. In total we obtained transaction and reputation data for auctions on eBay for three models of iPod by Apple, with closing dates between February 14 and February 28.

We further removed the transactions belonging to either of the following cases and are left with 135 valid auction transactions.

- The item for sale is not iPod per se, but parts or accessories for iPods;
- There was no bid in the entire auction period;
- The auction ended with buy-it-now;
- The auction was relisted because reserved price was not met;
- The item is no longer for available for sale;
- The auction was terminated due to errors in the listing.

4.2 Variables used in Empirical Analysis

The dependent variable, denoted by *WinningPrice*, is the second highest bid plus an increment.

Since a seller can earn her previous feedback from either a selling behavior or a buying behavior, we denote the seller reputation variables by *AllPos, AllNeg, AllNeu, AllPosRatio, SellPos, SellNeg, SellNeu, SellPosRatio, BuyPos, BuyNeg, BuyNeu, and BuyPosRatio.* Each buyer or seller may get multiple comments from a unique customer. In order to eliminate the bias from the comments from a set of particular customers and to reduce the effect of reputation manipulation, we counter only the first comment left by a customer to evaluate the above reputation variables. This is common in the literature, and it is also how eBay calculate and report users' reputation. Variables *AllPos, AllNeg, AllNeu* and *AllPosRatio* are, respectively, the number of positive, negative and neutral comments from unique registered users and the ratio of positive comments among all comments from unique registered users. *SellPos, SellNeg, SellNeu* and *SellPosRatio* are, respectively, the number of positive, negative and neutral comments from her unique buyers and the ratio of positive comments among all comments from unique buyers. *BuyPos, BuyNeg, BuyNeu,* and *BuyPosRatio* are respectively, the number of positive, negative and neutral comments from her unique sellers and the ratio of positive comments among all comments from unique sellers.

We select the 3rd generation, 15G iPod MP3 players made by Apple Inc. The standard item comes with accompanying accessories like Apple earphones, AC adapter, firewire cable, PC firewire adapter. The retail price for a brand new product is $299.00. The auction items in our sample are homogeneous except accessories and degree of usage. Extra accessories will increase the value of the item package and a brand new iPod will be valued higher than a used one. So we control the accessories and the new or used property of the auction items with two variables *Accessories* and *NIB*. The variable *Accessories* refers to the value of the extra accessories included with the item sold. The value of the accessories was obtained from the Apple online store as the market price. *NIB* is a dummy variable. *NIB* takes the value one if the item is listed as new-in-box and zero otherwise.

The remaining variables defining the auction's characteristics are: *NumofBids, Length, FirstBid, Paypal, Gallery, HighLight, Bold*, and *Reserve*. *NumofBids* refers to the total number of bids showed up in the bid history of an auction. Since we removed those withdrawn or no-bid transactions, there are at least one bid for each transaction: *NumofBids* is greater than or equal to one. *Length* is the number of days an action listing lasts. *FirstBid* is the starting bid amount the seller chooses. *Paypal, Gallery, HighLight, Bold*, and *Reserve* are dummy variables. *Paypal* takes one if the seller accepts payment though Paypal or credit cards, which provides certain degree of payment protection to the buyers. *Gallery, HighLight,* and *Bold*, respectively, referring to whether the seller put a thumbnail photo, highlighted the listing with an eye-catching colored band, or boldfaced the listing in search and listing pages. These variables control the sellers' effort to grab the buyers' eyeball and provide more information about the product to reduce the risks from product quality. We use dummy variable *Reserve* to indicate whether the seller put a reserve price or not.

4.3 Summary Statistics

Table 2 provides descriptive summary of the statistics for the variables used in our analysis.

The winning price ranged from a high of \$345.00 to a low of \$223.50. The mean trading price of \$283.13 is lower than the market price of \$299.00 posted on Apple online store. The eBay traders receive about 50 times of the number of comments as a seller than as a buyer.

The unknown type feedbacks are the feedbacks that are not classified as from buyer, or seller. It counts for 6.7 percent of all the feedbacks of the sellers in our dataset. Since all feedbacks from June 21st 2001, are classified as from seller, or from buyer. So all unknown type feedback in our dataset are feedbacks left before June 21st 2001. For those sellers who have unknown type comments, we read through the comments and classified the sources manually.

The data is supportive of our main hypothesis, that is,

1. The sellers are not pure sellers; they are also buyer in some time. In our dataset, 14% of the time these sellers are buying from eBay.
2. Comparing with their buying transactions, the sellers got distortional higher negative feedback ratio in their selling transactions, 1.20 percent vs. 0.69 percent, i.e., the negative ratio of the users as seller is 74 percent higher than the negative ratio as buyer.
3. If we look at the seller's negative feedback ratio when they are indeed seller, instead of from all transactions, it is higher. In this case, it increases from 1.13 percent to 1.20 percent.

5. Results

We derive our results from the multivariate regression model.

$$\begin{aligned}\ln(Winning\,\mathrm{Pr}ice_i) = \beta_0 + \beta_1 \ln(SellPos_i + 1) + \beta_2 \ln(SellNeg_i + 1) + \beta_3 \ln(BuyPos_i + 1) \\ + \beta_4 \ln(BuyNeg_i + 1) + \alpha \sum X_i + \varepsilon_i\end{aligned} \tag{4}$$

where X_i represents all the product characteristics and auction characteristics: ln(*Accessories*+1), *NIB, NumofBids, Length, FirstBid, Paypal, Gallery, Highlight, Bold*, and *Reserve*.

Table 3 reports the results of our empirical analysis. We find that both the positive and the negative comments the seller received during her previous sales have significant effect on the bidding price. A 10 percent increase in the positive selling record will increase the bidding price by 0.29 percent or around $0.82, while a 10 percent increase in the negative selling record will decrease the winning price by 0.5 percent or around $1.41. Suppose an iPod seller has one positive comment and one negative comment from previous buyers. No matter how many positive comments she has received from previous sellers, one more positive selling comment will increase her expected winning price by about $8.19 and one more negative selling comment will reduce her expected winning price by about $14.11. The results also show that negative ratings are paid more attention and therefore have higher impact to the winning price than positive ones do.

The comments earned from the sellers' previous purchases do not affect the winning price significantly. And the signs of the impact are opposite to our expectation, that is, an increase in the positive buying record will decrease the winning price and vice versa, which does not make sense.

The above results further empirically support our hypothesis that buying reputation does not affect the seller's goodwill in a selling transaction. A rational buyer will only consider the seller's selling record when bidding for the item.

The winning price increases significantly with the value of accessories and whether the product is new or not, and auction properties such as accepting paypal, number of bids, and the value of first bid.

We also find that the alternative functional forms, for example, replace the ln(*WinningPrice*) with *WinningPrice*, does not affect the estimation results and significance of the variables.

6. Conclusion

Trust building in the online community is a crucial issue that relates to the survivability of the Internet market. We build a simple model to illustrate our propositions about the online feedback mechanism adopted by some major consumer-to-consumer online auction websites. That is, given the flexibility in identity creation and switching in the Internet environment, a bidder will separate a seller's selling reputation from her buying reputation.

We take the theory to the trading data on eBay.com---a major online auction web site and get the following major results:

(1) The numbers of a seller's positive and negative comments from her buyers solely are significantly correlated with the bidding price of her sales transactions;

(2) The numbers of a seller's positive or negative comments earned in her purchasing transactions are not significant in explaining the bidding price of her sales transactions;

(3) Negative comments are weighted more heavily than positive ones.

EBay has added the indication of the types of transactions in the feedback history pages since June 2001. Moreover, starting from January 2004, tabs that grouped the feedbacks from sellers and from buyers were included in the feedback history pages. These practices show that eBay has realized the importance of separating the selling feedbacks from the buying feedbacks. Since negative feedbacks are paid more attention and have greater impact on the bidding prices of the items, based on our and other research conclusion, eBay should give the exact feedback score, typically, number of negative feedbacks, from the selling feedback history.

We are testing our hypothesis with transactions of other categories of items on eBay.com. It would be interesting if we could study with the data from the online trading web sites from other countries, for example, EachNet.com in China.

Selected References

Avery, C., Resnick, P. and Zeckhauser, R. "The Market for Evaluations," *American Economics Review* (89:3), 1999, pp. 564-584.

Ba, S. and Pavlou, P. "Evidence of the Effect of Trust Building Technology in Electronic Markets: Price Premiums and Buyer Behavior," *MIS Quarterly* (26:3), 2002, pp. 1-26.

Bajari, P. and Hortacsu, A. "Winner's Curse, Reserve prices and Endogenous Entry: Empirical Insights from eBay Auctions," *Rand Journal of Economics* (34:2), 2003, pp. 329-355.

Dellarocas C. "The Digitalization of Word-of-mouth: Promise and Challenges of Online Feedback Mechanisms," *Management Science* (49:10), 2003, pp. 1407-1424.

Cripps, M., Mailath, G. and Samuelson, L. "Imperfect Monitoring and Impermanent Reputations," Penn Institute for Economic Research Working Paper 02-021 (available at: http://www.econ.upenn.edu/Centers/pier/Archive/02-021.pdf), 2002.

Dewan, S. and V. Hsu, "Trust in Electronic Markets: Price Discovery in Generalist Versus Specialty Online Auctions," Working paper, (http://databases.si.umich.edu/reputations/bib/papers/Dewan&Hsu.doc) Jan 2001.

Eaton, D. H. "Valuing Information: Evidence from Guitar Auctions on eBay," Working paper, Murray State University, Department of Economics Working Paper #0201 (available at: http://campus.murraystate.edu/academic/faculty/david.eaton/workpaper0201.pdf), 2002.

Friedman, E. and Resnick, P. "The Social Cost of Cheap Pseudonyms," *Journal of Economics and Management Strategy* (10:1), 2002, pp. 173-199.

Fudenberg, D., and Levine, D. "Maintaining a Reputation when Strategies are Imperfectly Observed," *Review of Economic Studies* (59), 1992, pp. 561–579.

Houser, D. and Wooders, J. "Reputation in Auctions: Theory and Evidence from eBay," Working Paper, The University of Arizona Department of Economics Working Paper 00-01, 2001 (available at: http://info-center.ccit.arizona.edu/~econ/working_papers/Internet_Auctions.pdf).

Kalyanam, K. and McIntyre, S. "Returns to Reputation in Online Auction markets," Santa Clara University Retail Workbench Working Paper W-RW01-02, 2001.

Kauffman, R. J., and Wood, C. "Running up the Bid: Modeling Seller Opportunism in Internet Auctions," *Proceeding of the Sixth Americas Conference on Information Systems*, M. Chung (ed.), Long Beach, CA, August 2000, pp. 929-936.

Keser, C. "Trust and Reputation Building in E-Commerce," Scientific Publication 2002s-75, Center for Interuniversity Research and Analysis on Organizations (CIRANO), Montreal, Canada (available at: http://www.cirano.qc.ca/pdf/publication/2002s-75.pdf), 2002.

Lee, Z., Im, I. and Lee, S. "The Effect of Negative Buyer Feedback on Prices in Internet Auction Markets," *Proceedings of the 21st International Conference on Information Systems*, Brisbane, Australia, 2002, pp286-287.

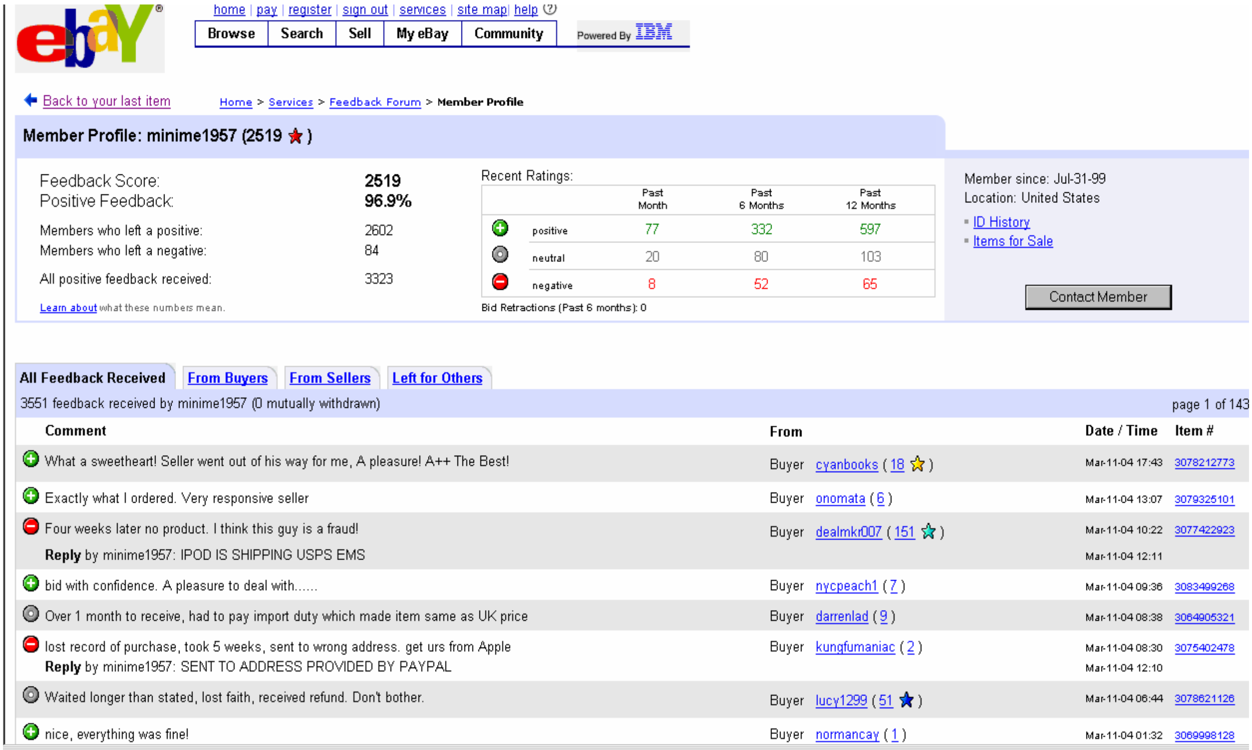
McDonald, C. G. and Slawson, V. C. Jr. "Reputation in an Internet Auction Market," *Economic Inquiry*, (40:3), 2002, pp. 633-650.

Melnik, M. I. and Alm, J. "Does a Seller's Reputation Matter? Evidence from eBay Auctions," *Journal of Industrial Economics*, 50 (3), 2002, pp. 337-349.

Resnick, P., and Zeckhauser, R. "Trust Among Strangers in Internet Transactions: Empirical Analysis of eBay's Reputation System," in *The Economics of the Internet and E-Commerce*. Michael R. Baye, (eds.), Volume 11 of Advances in Applied Microeconomics. Amsterdam, Elsevier Science. 2002.

Tadelis, S. "The Market for Reputations as an Incentive Mechanism." *Journal of Political Economy* (92:2), 2002, pp. 854-882.

Figure 1. Examples of Feedback Mechanism Used in eBay and Yahoo! Auctions.



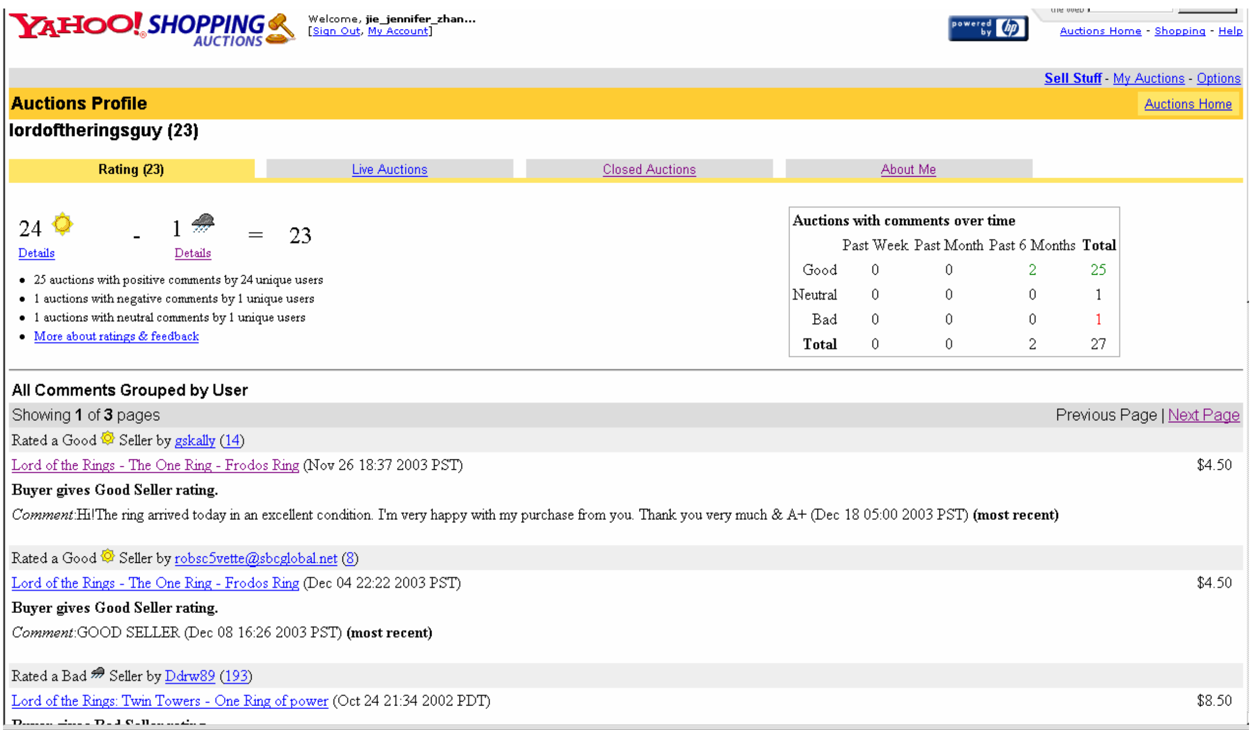


Table 2 Descriptive Statistics (N = 135)

	Variable	Mean	Std. Dev.	Min	Max
Dependent Variable	Winning Price	$283.13	20.37	$223.50	$345.00
Reputation Variables	SellPos	1200	1130	0	7483
	SellNeg	36	40	0	198
	SellNeu	51.6	55.4	0	189
	BuyPos	24.9	28.4	0	152
	BuyNeg	0.51	0.58	0	4
	BuyNeu	0	0	0	0
Item Characteristics	Accessories	4.56	20.99	0	200
	NIB	0.66	0.48	0	1
Auction Characteristics	NumofBids	22	9.2	1	50
	Length	3.4	1.9	1	10
	FirstBid	$30.53	71.63	$0.01	$289.99
	Paypal	0.88	0.33	0	1
	Gallery	0.66	0.47	0	1
	Highlight	0.01	0.09	0	1
	Bold	0.24	0.43	0	1
	Reserve	0.10	0.30	0	1

Table 3 Estimation Results (t-statistics in parentheses)
Dependent Variable = ln(WinningPrice)

Independent Variable	I	II	III	IV	V	VI	VII	VIII	IX	X	XI
ln(SellPos+1)	0.007*	0.018***	0.028***	0.030***	0.028***	0.027***	0.028***	0.029**	0.028**	0.025***	0.024***
	(1.73)	(3.05)	(4.59)	(4.33)	(3.97)	(3.92)	(4.05)	(4.14)	(3.80)	(3.25)	(3.14)
ln(SellNeg+1)	-0.020***	-0.047***	-0.052***	-0.054***	-0.052***	-0.049***	-0.049***	-0.050***	-0.049***	-0.047***	-0.042***
	(-3.52)	(-3.94)	(-3.26)	(-4.49)	(-4.33)	(-4.07)	(-4.12)	(-4.20)	(-3.75)	(-3.56)	(-3.25)
ln(BuyPos+1)		-0.013	-0.012*	-0.013*	-0.052	-0.005	-0.006	-0.006	-0.005	-0.003	-0.003
		(-1.96)	(-1.66)	(-1.73)	(-0.88)	(-0.59)	(-0.79)	(-0.68)	(-0.54)	(-0.39)	(-0.31)
ln(BuyNeg+1)		0.093**	0.072*	0.075*	0.056	0.044	0.049	0.065	0.064	0.059	0.046
		(2.43)	(1.77)	(1.83)	(1.33)	(1.04)	(1.16)	(1.49)	(1.43)	(1.29)	(1.05)
ln(Accessories+1)			0.024***	0.023***	0.027***	0.026***	0.027***	0.027***	0.027***	0.028***	0.030***
			(3.90)	(3.83)	(4.29)	(4.15)	(4.30)	(4.35)	(3.95)	(4.12)	(4.39)
FirstBid				0.0001	0.0001	0.0002	0.0002	0.0001	0.0001	0.0001	0.0003**
				(0.57)	(1.34)	(1.50)	(1.55)	(1.18)	(1.07)	(1.17)	(2.21)
NIB					0.043*	0.044**	0.050**	0.041*	0.041*	0.045*	0.046**
					(1.92)	(2.01)	(2.22)	(1.76)	(1.75)	(1.90)	(2.01)
Paypal						0.027	0.028*	0.032*	0.033*	0.035**	0.032*
						(1.60)	(1.69)	(1.90)	(1.90)	(2.04)	(1.88)
Length							0.005	0.003	0.003	0.004	0.004
							(1.28)	(0.82)	(0.82)	(1.12)	(1.16)
Gallery								-0.025	-0.027	-0.023	-0.018
								(-1.35)	(-1.34)	(-1.14)	(-0.93)
Bold									0.006	0.003	-0.001
									(0.22)	(0.14)	(-0.03)
Reserve										-0.031	-0.023
										(-1.34)	(-0.99)
NumofBids											0.002**
											(2.38)
Constant	5.651	5.659	5.615	5.609	5.572	5.542	5.518	5.537	5.537	5.538	5.488
	(361.50)	(336.79)	(279.48)	(241.26)	(187.22)	(158.41)	(138.64)	(131.21)	(130.53)	(131.05)	(118.53)
R^2	0.109	0.153	0.305	0.307	0.331	0.346	0.357	0.368	0.368	0.379	0.413
Adj. R^2	0.095	0.127	0.273	0.268	0.286	0.297	0.301	0.307	0.300	0.306	0.336

Note: *** --- p value < 0.01, ** --- p value < 0.05, * --- p value < 0.10.