

Reputation, Trust, and Rebates: How Online Auction Markets Can Improve Their Feedback Mechanisms

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Revision Date: October 30, 2006

Abstract

Trust and trustworthiness are crucial to the survival of online markets, and reputation systems that rely on feedback from traders help sustain trust. However, in current online auction markets only half of the buyers leave feedback after transactions, and nearly all of it is positive. In this paper, I propose a mechanism whereby sellers can provide rebates to buyers contingent on buyers provision of reports. Using a game theoretical model, I show how the rebate incentive mechanism can increase reporting. In both a pure adverse selection model, and a model with adverse selection and moral hazard, there exists a pooling equilibrium where both good and bad sellers choose the rebate option, even though their true types are revealed through feedback. In the presence of moral hazard, the mechanism induces bad sellers to improve the quality of the contract.

1 Introduction

Coase (1988) points out that “fraud increases the profit of the defrauding firm but reduces customers, thus reduces its future business; while in a highly mobile society, it is obvious that there is likely to be less honesty.” The problem of developing trade among remote traders has been discussed for as long as remote trade itself. Possible solutions include law enforcement, judicial institutions, and community enforcement. In many cases, the value of the transactions are too low to be worth settling in court; and in some cases institutions are only responsible for information. In the absence of legal enforcement, reputation plays a crucial role in supporting trust in remote trade (e.g., Greif (1993), Milgrom et al. (1990)).

*Thanks to the Department of Economics and Institute for Mathematical Behavioral Science Summer Fellowship for support. I am grateful for comments on earlier drafts from Donald Saari, Yannis Bakos, Jiawei Chen, Linda Cohen, Sanjeev Dewan, Amihai Glazer, Jun Ishii, Michael McBride, Stergios Skaperdas, Hal Varian, Kevin Zhu, members of my weekly discussion group, and participants in IT Economics workshop at NYU, 2006 IMBS graduate students conference, and 2006 Western Economic Association conference. I am of course responsible for all remaining errors.

The Internet has changed the long-term relationships of a brick-and-mortar world. Online commerce markets, especially online auction markets, share essential features of remote trade: buyers and sellers are remote and anonymous to one another, they know no more about each other than what they see online, transactions tend to be geographically diffused, and it is very easy to exit and enter these markets by changing online identities. As the IBM 2002 Global Service Executive Technology Report pointed out, “the value of e-business is fundamentally tied to achieving the *trust* that allows us to rely on electronic information transmitted over the Internet ... specific services must be put in place to establish and help ensure trust before the full potential for e-commerce, collaboration, electronic markets and dynamic partnering can be realized.”¹ So, what makes traders believe they can trust trading partners to provide the service or payment as promised per an agreement made in cyberspace? How can online auction markets survive in the face of these trust issues?

According to a Federal Trade Commission (FTC) study (Anderson (2005)), online auction fraud complaints made up 41,796 out of 180,000 total complains filed with the FTC from January 2005 to June 2005, and consistently ranked near the top of the list for all fraud complaints filed with the FTC from 2000 to June 2005.² According to the complaints filed in 2004, the highest reporting rate, 17.6%, was for items costing between \$251 to \$500, followed by items costing \$1001 to \$2500 which came in at 15.2%.

Despite increasing online auction fraud, the online auction market is still thriving. According to an ACNielsen study on Global Consumer Attitudes Towards Online Shopping in October 2005, more than 627 million people have shopped online, including over 325 million in September 2005 alone. The latest report about online auctions by Forrester Research forecasts that online consumer auctions sales will reach \$65 billion by 2010, accounting for nearly one-fifth of all online retail sales.³ eBay, the largest online auction site in the world, has 180.6 million registered users, of which 71.8 million are active.⁴ In 2005, there were 1.9 billion items listed, with a Gross Merchandise Volume,

¹Available online at: <http://www-1.ibm.com/services/au/igs/pdf/g510-3262-00-etr-trust-opening-opportunities.pdf> (Accessed on Jan 10, 2006)

²The FTC report shows that the dollar value amount of the complaints on online auction fraud was 3.88 million which comprised 61% of the total dollar value of fraud complaints filed to the FTC in 2004.

³Forrester Research, “US Online Auction Sales, 2005 to 2010”, Report (October, 2005), Available online at <http://www.forrester.com/Research/Document/Excerpt/0,7211,37848,00.html> (accessed on Jan 28, 2006).

⁴Registered users are the cumulative total of all users who have completed the registration process on one of eBays trading platforms. Active users are all users, excluding users of Half.com, Internet Auction, Rent.com, Shopping.com, and eBay classified web sites, who bid on, bought, or listed an item within the previous 12-month period. Includes users of eBay EachNet in China and eBay India since the migration to the eBay platform in September 2004 and April 2005, respectively.

the total value of all successfully closed listings on eBays trading platforms, of \$44.3 billion.⁵

A critical reason for the success of online auction sites is the use of an online feedback system as a reputation system to help sustain trust in online markets (Resnick and Zeckhauser (2002), Shankar and Sulta (2002), Ba et al. (2002), Wang and Emurian (2005), Dellarocas (2004), Dellarocas (2005), Jøsang et al. (2005)).⁶ However, current online reputation systems are not perfect and online auction fraud still account for a significant proportion of the complaints filed with the FTC. There are several major problems with online reputation systems, including low incentives for providing feedback, bias toward positive feedback, abuse of the reputation system, and traders changing identities. If there is no accurate information about sellers' past transaction history, good sellers might be driven out of the market akin to the lemon car market of Akerlof (1970). Such problems would destroy the trust and trustworthiness in online markets, thus limiting their growth.

This paper focuses on remedying the problem of a lack of incentives to provide feedback reports. Once all feedback can be observed the problem of bias towards positive feedback will be solved as well. By giving sellers an option to provide rebates (not necessarily in monetary form) contingent on buyers leaving feedback, we find that such an incentive mechanism will lead to full information revealing and thus help buyers identify the sellers' types and induce sellers to behave cooperatively.

The layout of this paper is as follows. In section 2, we review the literature on asymmetric information and reputation mechanism models. In section 3, we examine the current reputation system in eBay as an example of an online market reputation system,⁷ and then identify potential problems of the system. In section 4, we use a simple game to illustrate the trust problem in online trade and illustrate how the online reputation systems work. In section 5, we propose an rebate incentive mechanism to overcome the lack of incentives to report problem. We discuss possible extensions of the incentive mechanism, for example, changing the identities issue and including moral hazard into the model in section 6. The conclusion and possible applications are provided in section 7.

⁵eBAY, "Forth Quarter and Full Year 2005 Financial Results," Available online at <http://investor.ebay.com/financial.cfm> (accessed on Feb 10, 2006)

⁶Not only auction sites but also online resellers use feedback systems to help sustain trust (for example, Reseller-ratings.com, Pricegrabber.com). This paper considers a special case of auction sites.

⁷eBay's reputation system is the most studied. Dellarocas (2001) and Li (2006) suggest that eBay's binary rating system (positive rating and negative rating) functions at least as well as the scale rating system (e.g., rating from 1-5).

2 Literature Review

Asymmetric information on the quality of products or sellers has a tremendous impact on market exchange. Much of the literature points out that opportunism activities exist under asymmetric information (e.g., Akerlof (1970), Klein and Leffler (1981), Shapiro (1982), Shapiro (1983), Kauffman and Wood (2000)). Reputation plays an important role in inducing agents to cooperate in an asymmetric information setting (e.g., Fudenberg and Levine (1992), Kreps and Wilson (1982), Kreps (1995), Celentani and Pesendorfer (1996), Battigalli and Watson (1997), Levine and Martinelli (1998), and Kandori (1992)).

In general the two types of asymmetric information models are the adverse selection model and the moral hazard model. Using bilateral trade as an example, in adverse selection models, nature begins the game by choosing the sellers' type (e.g., some sellers are more capable or honest than others), unobserved by buyers. A seller and a buyer then agree to a contract, and the seller behaves according to his type (e.g., careful sellers consistently pack products carefully and ship it, whereas careless sellers often fail to deliver the product; or honest sellers consistently advertise the products according to the true conditions, whereas dishonest sellers often fail to provide the true condition of the product). In the moral hazard model, a buyer and a seller begin with symmetric information and agree upon a contract, but then the seller takes an action unobserved by the buyers (e.g., the seller has an incentive to undercut quality of a product to maximize his profit).

Reputation mechanisms play different roles in each of these two settings. Dellarocas (2003a) points out that in an adverse selection setting, the role of a reputation mechanism is to help the community learn the (initially unknown) attributes of community members (such as their ability, honesty, etc.); while in a moral hazard setting, the objective of reputation mechanisms is to promote cooperative and honest behavior among self-interested economic agents by the threat of future punishment (e.g., in the form of lower bids following the posting of a negative rating on a trader's reputation profile). As Cabral (2005) summarizes, typical reputation mechanism models that create "reputation" (i.e., when agents believe a particular agent *to be* something) are based on Bayesian updating of beliefs and, in an adverse selection setting, possibly signaling (for example, Klein and Leffler (1981) and Shapiro (1983)). There are other essential reputation models in which "trust" (i.e., when agents expect a particular agent *to do* something) is created through repeated interaction and the possibility of "punishing" off-equilibrium actions in a moral hazard setting (Kreps and Wilson (1982), Milgrom and Roberts (1986), Diamond (1989)). MacLeod (2006) and

Jøsang et al. (2005) also provide surveys on trust and reputation.

In an online market, the reputation system is the main institution to induce traders to behave cooperatively. Since the online reputation system controls the content and format of aggregated information it publishes, it is important to design an incentive mechanism that will elicit truthful feedback. There is much literature pertaining to the topic of mechanism design. Resnick et al. (2000) and Dellarocas (2006) provide overviews on reputation mechanisms. Some of the literature focuses on the efficiency of online reputation mechanism (Dellarocas (2001)), others design mechanisms to deal with untruthful reporting problems, such as bad mouthing and ballot stuffing (Bhattacharjee and Goel (2005), Dellarocas (2004))⁸.

Several papers design mechanisms to induce sellers to behave cooperatively. Ba et al. (2002) suggests the Trusted Third Party (TTP) mechanism to issue certificates to sellers and buyers. Dellarocas (2003b) proposes charging a listing fee contingent on a sellers announced expected quality and rewarding the seller contingent on both his announced quality and the rating posted for that seller by the winning bidder for that listing. Miller et al. (2005) proposes the peer prediction method in which the center (online market) provide awards to feedback providers. Dellarocas and Wood (2006) provide a sophisticated computational mechanism to repair distortions introduced by reporting bias. These mechanisms are impressive, but each has some disadvantages. Ba et al.'s (2002) mechanism can induce cooperative behavior if both buyers and sellers obtain the verifications from the TTP, and it imposes extra transaction cost to buyers. Dellarocas's (2003b) mechanism requires all buyers to report, while Miller et al.'s (2005) requires the market maker to provide incentives to rating providers. Finally, Dellarocas and Wood's (2006) requires buyers to take missing feedback into consideration, though it is very difficult for an average buyer to get this information.

The mechanism proposed in this paper addresses the shortcomings of these existing mechanisms. The objective of this paper is to design a mechanism to induce buyers to report and have a *self-sustaining* market where only sellers and buyers are involved with minimal transaction costs. We propose giving sellers an option to provide a rebate to cover the reporting cost to a buyer.⁹ This will provide an incentive for buyers to provide feedback without any loss to the online market maker. The only cost an online auction market might have is to produce this option for sellers, which may not be substantial.

⁸Ballot stuffing occurs when a seller colludes with other buyers to undertake fake transactions in order to enhance her reputation. Bad mouthing occurs when a seller is targeted by a group of buyers to deliberately lower her reputation.

⁹The rebate is not necessary in monetary form, please see section 5.4 for more details about the rebate form.

3 Current Online Auction Market Reputation System

There are several online auction markets, such as eBay, Amazon Auctions, and Yahoo! Auctions. In this section, we examine how well the reputation systems work in these markets.

3.1 How Well does eBay’s Reputation System Work?

eBay might be best thought of as an e-commerce website which provides a “virtual” flea market of new and used merchandise for buyers and sellers worldwide to trade via auctions.¹⁰ eBay only provides a platform for sellers and bidders to interact, and plays no role in the actual exchange of items at the end of the auction. The winning bidders and sellers complete the transaction by themselves. The founder of eBay, Pierre Omidyar, announced that a feedback system was initiated on eBay’s AuctionWeb (www.auctionweb.com) on Feb 26, 1996.¹¹ After each transaction is completed, the seller and the winning bidder can send feedback about the other party to eBay.¹² The rating can be +1 (positive), 0 (neutral), and -1 (negative), along with brief textual comments. Each trader has a profile which contains this reputation information.



Figure 1: Ebay Feedback

As shown in Figure 1, there are several summary statistics in the current member’s profile. “Feedback Score,” which always appear next to the trader’s ID, represents the number of eBay members who have completed a transaction and left feedback with this particular member.¹³ The score include feedback from both buying and selling and the difference of the number of members

¹⁰eBay launched a set-price site, eBay Express (http://www.express.ebay.com/), in April 2006 to supplement bid-and-wait online auctions. Cited from Wall Street Journal April 24, 2006.

¹¹An early version of the AuctionWeb home page is available at http://forums.ebay.com/db2/thread.jspa?threadID=410122850. eBay was launched on Labor day, 1995 (accessed on Jan 28, 2006).

¹²eBay encourages sellers to leave feedback about buyers once they receive payment, but some sellers hold their feedback until buyers report and thus use it as a means of retaliation or reciprocation.

¹³This number may be different then the number of total transactions of the particular member. If there is no feedback for a certain transaction, a future trader can not know the existence of the transaction.

who left a positive rating and the number of members who left a negative rating. If a member has had several transactions with the seller and leaves more than one positive rating, eBay will still only count it once in the feedback score. In the example shown above, the feedback score is $78045 - 2946 = 75131$. “Positive Feedback” represents positive ratings left by members as a percentage. “Members who left a positive” and “Members who left a negative” represent the number of unique members who have given the seller a positive rating or a negative rating, respectively. “All positive feedback received” represents the total number of positive feedback received for all transactions, including repeated trade partners.¹⁴ “Recent ratings” table shows all of the ratings left for this member during the past month, 6 months, and 12 months. In addition, eBay also provides the entire feedback record with information on both buyer and seller transactions, time of the comment, transaction ID and textual comments.¹⁵ Since eBay’s feedback system launched in 1996, it has made many changes. Please see the appendix for more details.

Many researchers have studied the effectiveness of the eBay reputation system. Many empirical papers estimate the market value of reputation and quantify distortion from asymmetric information in the online auction market. Resnick et al. (forthcoming) and Bajari and Hortaçsu (2004) provide a comprehensive survey of the empirical analysis of the reputation mechanism used by eBay. For instance, some papers examine the components of eBay’s feedback profile that can better explain buyers’ behavior (Ba and Pavlou (2002), Lee and Malmendier (2005), Dewan and Hsu (2004)); some consider the effect of a seller’s feedback profile on the probability of sale (Eaton (2002), Livingston (2005)). In addition, while many empirical studies of eBay’s reputation mechanism tend to focus on a buyer’s response to the published feedback, some papers also investigate the effect of a seller’s feedback profile on the probability of sale (Bajari and Hortacsu (2003), Eaton (2002), Livingston (2005), Resnick and Zeckhauser (2002)). Only two papers Cabral and Hortaçsu (2006), and Jin and Kato (2005) focus on the seller’s equilibrium behavior influenced by incentives created through eBay’s feedback system. Resnick et al. (forthcoming) point out the omitted variable problem in the previous research and use controlled experiments to address this problem by holding constant the quality of goods, skill at listing a product, responsiveness to inquiries, and all other potential confounding factors in previous observational studies. They find that buyers are willing to pay 8.1% more for pairs of lots of vintage postcards, from an established seller rather than new vendors, and

¹⁴If there is no feedback for a certain transaction, then future potential buyers do not know about the transaction.

¹⁵Transaction data can be only stored on eBay for 90 days, so it is impossible to track the transaction. The information was accessed from eBay web site at <http://pages.ebay.com/help/feedback/evaluating-feedback.html> on Jan 28, 2006.

surprisingly, one or two negative feedback for new sellers does not affect buyers' willingness-to-pay. As summarized in Dellarocas (2003a), the principal conclusions derived from a collective reading of these works are:

- Feedback profiles seem to affect both prices and the probability of a sale. However, the precise effects are ambiguous; different studies focus on different components of eBay's complex feedback profile and often reach different conclusions.
- The impact of feedback profiles on prices and probability of sale is relatively higher for more expensive products.
- Among all the different pieces of feedback information that eBay publishes on a member, the components that seem to be most influential in affecting buyer behavior are the overall number of positive and negative ratings, followed by the number of recently posted negative comments (i.e., in the last seven days or last month).

Empirical results of the current online reputation systems indicate that such a system seems to work, though there are several potential problems, as discussed below.

There are several potential problems regarding the current reputation mechanism systems in the online markets. Resnick and Zeckhauser (2002) report some interesting properties about the feedback score by using data from eBay:¹⁶

1. Most trading relationships are one-time deals: 89% of all buyer-seller pairs conducted just one transaction during the five-month period covered by the data set.
2. Buyers left feedback on sellers 52.1% of the time; sellers on buyers 60.6% of the time.
3. Feedback is overwhelmingly positive; of feedback provided by buyers, 99.1% of comments were positive, 0.6% was negative, and 0.3% was neutral.

From these statistics, we can conclude that, first, the participation rate of leaving feedback is not very high. Once the transaction is completed, the transaction partners usually have no direct incentive for leaving feedback about the other party. There may be costs associated with reporting such as the opportunity cost of typing comments, or the possibility of being retaliated against by the other party for leaving negative feedback. Second, feedback is positively biased. This might be

¹⁶Similar statistics of positive feedback have been shown in Cabral and Hortag su (2006), Dellarocas and Wood (2006) and Klein et al. (2005) as well.

because of an exchange of courtesies, or to avoid retaliation. Dellarocas and Wood (2006) provide rigorous evidence for the presence of reciprocation and retaliation among eBay traders and find that the true positive rating is 86.5% instead of 99%. Third, there is the issue of low cost of changing one's online identity. Traders with a bad reputation can easily change their online ID and start over as a "new" member. There are also many other problems with the online feedback system, for example, there exists a market of reputation in which traders can manipulate their reputation score by participating in the market on eBay (Brown and Morgan (2006)),¹⁷ abuse of the reputation system such as unfair rating and ballot stuffing. In this paper, we focus on solving the first three problems, especially focusing on solving the problems of lack of incentives to provide feedback and feedback biased towards the positive.

3.2 How Well Other Online Auction Market Reputation Systems Work?

Besides eBay, Yahoo! and Amazon also launched auction sites, but their market sizes are much smaller than eBay.¹⁸ The reputation system on Yahoo auction site is very similar to eBay's, but is less user-friendly. For example, to find feedback of a transaction left by both parties, we need to look up the feedback from each party's feedback profile. It is not easy to distinguish selling and buying activities for a trader. Yahoo! auction also does not show the exact time when the feedback is left and when it is posted by Yahoo!. The reputation system on the Amazon auction site is scaled from 1 to 5, with a higher number representing better feedback. As Li (2006) finds, the Amazon's scaled feedback system is less robust against strategic voting than the binary system adopted by eBay.¹⁹ Amazon auction uses unilateral reputation system, only buyers can leave feedback about sellers, not the other way around. In this sense, eBay's reputation system is the most sophisticated among these three online auction markets. We use eBay's reputation system to set up the reputation model in the latter section.

¹⁷Some sellers in eBay sell low-prices, valueless items designed only to artificially enhance the sellers' feedback ratings.

¹⁸In 2001, eBay's market share was 64.3%, Yahoo! Auction's market share was 2.4%, and Amazon Auction's was 2%.

¹⁹Amazon's rating system is less stable to strategic voting behavior. For example, if a strategic voter's true rating is 2 (slightly negative), he can exaggerate his negative opinion by leaving a 1 (strong negative) instead of a 2 which is his true opinion on Amazon.com

4 A Model of Trust and Reputation in Online Auction Markets

Online auction transactions are anonymous, easy to enter and exit, and geographically diffuse. We use an adverse selection model to illustrate the trust problem and the reputation system in the current online auction market, and we incorporate moral hazard into the model in section 6. In this section, we present a model with adverse selection and use eBay's current reputation system as an example of an online reputation system in the model. In the next section, we propose a way to improve the current reputation system.

Since most online transactions require sellers to receive payment before sending the product, we only consider the case where sellers have an incentive to commit fraud.²⁰ Experimental results show that when players play repeated Prisoners' Dilemma games in fixed pairs (play with the same opponents for every period), cooperation is more likely to occur; while in randomly matched pairs, cooperation is less likely to occur (Schmidt et al. (2001)). A crucial reason for lack of cooperation in randomly matched pairs is that the information about the opponents' past history is not fully revealed in the case of random matched pairs. This suggests that one way to induce players to cooperate when they are randomly matched is through the reputation mechanism (Kandori (1992), Schmidt et al. (2001), and Bolton et al. (2003)). Bolton et al. (2003) examine the cooperation level in a trust game under first order information (what players did last time) and second order information (what the player's rival did before he met this rival, and what players did the last time). The results suggest that the more information about reputation, the more cooperation. Thus, reputation plays an important role in sustaining cooperation. The following model illustrates how the current reputation systems work in the online auction markets.

4.1 A Model of Adverse Selection and Reputation System

The difference between a conventional retail market and an auction market is that the price is decided by buyers through bidding in the auction market. To capture the essence of the online reputation system, we first make some assumptions. Suppose there are M sellers and N buyers in the entire market where $N \gg M$, and the sellers live infinitely. We focus on one auction listing where a seller (s) lists the same good (g) at each period. There are two realizations of the transaction: high quality level (Q_H) and low quality level (Q_L). High quality means that the good is received by

²⁰Most complaints filed with the FTC as Internet auction fraud report problems with sellers who "fail to send the merchandise," "send something of lesser value than advertised," or "fail to deliver in a timely manner," "fail to disclose all relevant information about a product or terms of the sale." For more information, please see: <http://www.ftc.gov/bcp/online/pubs/online/auctions.htm> (accessed on Jan 20, 2006).

the buyer, the quality of the good is the same as the seller promised, and that the good is shipped on time. A transaction is low quality if it fails any of these conditions. For each period, there are K buyers randomly drawn with replacement from the N potential buyers, the valuation of the good by the buyers V_b are uniformly distributed from 0 to 1, $0 < V_b(1) < V_b(2) < \dots < V_b(K) \leq 1$, the buyer K wins the bidding, and the price is settled at P . We use eBay as an example of the online auction market, and eBay uses the Vickrey auction method, i.e., the winning bidder pays the second highest bid, so $P = P(V_b(K-1)) < P(V_b(K))$. We assume that there are many bidders for each auction, and the winning bid is ξ higher than the second highest bid, and the winning bid equals to the willingness to pay for the winning bidder, so we use the highest bid to approximate the willingness to pay of the winning bidder, i.e., $P \approx P(V_b(K))$.²¹ Without losing generality, we assume that a good is worth 1 to the winning bidder if it is a high quality transaction (Q_H), and the good is worth 0 if it is a low quality transaction (Q_L). By this setting, the price of an item is determined by the reputation of a seller, and both seller and buyer know how the price is determined.²² After the bidding process, there is only one seller (s) and one buyer (b) in the transaction.

We assume there are two types of sellers, good type (G) and bad type (B). The commonly known proportion of good sellers are μ_0 , and the proportion of bad sellers are $1 - \mu_0$. The probability that a high quality transaction is provided by a good seller is α , and is β for a bad seller ($0 \leq \beta < \alpha \leq 1$). For example, the good sellers are very careful and honest, so they advertise the product according to the true condition, pack the good carefully and ship it on time; while the bad type sellers are lazy and dishonest. In this model, nature chooses the transaction outcomes for the sellers, so the sellers do not control the transaction outcomes. We will consider later the cases where the sellers can choose an effort level that will affect the transaction outcomes where adverse selection and moral hazard are combined in the later section.

The seller lives infinitely, and the K buyers randomly drawn from N buyers are different from period to period. Each period t consists of a sequence of moves in the following order:

1. Nature chooses the seller's type $\theta \in \{\theta_G, \theta_B\}$. The seller's type is chosen in the first period, and it persists for the rest of the game.

²¹We can also use the auction model in Cabral and Hortaçsu (2006) to show that the winning bid is an increasing function of buyer's willingness to pay.

²²The model is set up to appeal to the intuition coming from eBay. However, please notice the model is exactly the same for the listed price markets, such as pricegrabber.com, resellerratings.com. One way to think about it is that a seller set a fixed price for the item at the highest willingness to pay of the buyers in that market.

2. The buyers choose a bid at the expected value of the transaction, $P \geq 0$.
3. The seller chooses to accept or reject P based on his reservation price. If he rejects, the game ends. If he accepts, then the game continues to the next step. For simplicity, we assume the good seller's reservation price is $V_S^G \geq 0$ and the bad seller's reservation price V_S^B is 0.²³
4. Nature chooses the quality of the transaction that buyers get from different types of sellers, Q_H or Q_L . Transaction quality is a new draw in every period.

$q(\theta)$ = probability of providing Q_H .

$$q(\theta_G) = \alpha$$

$$q(\theta_B) = \beta$$

$$0 \leq \beta < \alpha \leq 1$$

5. After the transaction, buyer chooses now to review the transaction $\{NR, GR, BR\}$. Buyers can choose to give a good report/positive feedback (GR), a bad report/negative feedback (BR), or no report (NR); the net reporting cost is C for all buyers.²⁴ Assume buyers report honestly if they decide to report, i.e., GR for Q_H and BR for Q_L .²⁵
6. These are payoffs received for period t .

$$U_s(Accept) = P - 0 = P;$$

$$U_s(Reject) = 0;$$

$$U_b(P, NR, Q_H) = 1 - P;$$

$$U_b(P, NR, Q_L) = -P;$$

$$U_b(P, GR, Q_H) = 1 - P - C;$$

$$U_b(P, BR, Q_L) = -P - C.$$

4.2 Equilibrium Analysis

Under the reputation system, in each period, the new buyers, who are new to the seller but may not be new in the market, observe the reputation history of the seller. Equilibrium outcomes vary

²³In the listed price case, the second move is that the seller sets a price at the highest buyers' expected value of the transaction if it is higher than his reservation price, otherwise the seller sets the price at his reservation price. The third move is that the buyer chooses to buy or not buy.

²⁴ C is reporting cost net the reporting benefit. For example, the reporting cost may be the time and effort to leave feedback, and the benefit may be the self-satisfaction out of altruism. The net reporting cost is proportional to the price P . We can assume the net reporting cost is uniformly distributed between $-C$ (gain more benefit through leaving a report than reporting cost) and C . In order to induce everyone to report, we still need to overcome the highest net reporting cost C . Here, we assume everyone's reporting cost is C for simplicity reason.

²⁵since buyers do not have repeated transaction with the same sellers, there is no incentive for buyers to report dishonestly.

with the reporting cost. To see the impact of reporting cost on the reputation system, we consider three variations of the reporting costs in the model: no reporting cost, symmetric reporting cost, and asymmetric reporting cost, respectively.

4.2.1 Case 1: No Reporting Cost ($C = 0$)

First, we examine the case where there is no reporting cost, i.e., $C = 0$. The buyer's willingness to pay at period $t + 1$ is

$$P_{t+1} = \mu_t \alpha + (1 - \mu_t) \beta, \quad (1)$$

where μ_t is the belief of meeting a good seller at period t . For instance, at period $t = 1$, μ_0 represents the prior belief and the buyer's willingness to pay is $P_1 = \mu_0 \alpha + (1 - \mu_0) \beta$. If the buyer receives a Q_H product and reports GR (we assume buyers not only report, but also report honestly if there is no reporting cost) in period $t = 1$, the buyer in period $t = 2$ observes the reports and updates his beliefs on the seller's type by Bayes' rule, so the prior in period $t = 2$ is

$$\mu_1 = Pr(\theta_G | GR) = \frac{Pr(GR | \theta_G) Pr(\theta_G)}{Pr(GR | \theta_G) Pr(\theta_G) + Pr(GR | \theta_B) Pr(\theta_B)} = \frac{\mu_0 \alpha}{\mu_0 \alpha + (1 - \mu_0) \beta}.$$

If the buyer receives a Q_L product and reports BR in period $t = 2$, the buyer in period $t = 3$ observes the previous reports and updates his beliefs according to Bayes' rule, so the prior in the period $t = 3$ is

$$\begin{aligned} \mu_2 &= Pr(\theta_G | GR, BR) \\ &= \frac{Pr(BR | \theta_G, GR) Pr(\theta_G, GR)}{Pr(BR | \theta_G, GR) Pr(\theta_G, GR) + Pr(BR | \theta_B, GR) Pr(\theta_B)} \\ &= \frac{Pr(BR | \theta_G) Pr(\theta_G, GR)}{Pr(BR | \theta_G) Pr(\theta_G, GR) + Pr(BR | \theta_B) Pr(\theta_B)} \\ &= \frac{Pr(BR | \theta_G) Pr(GR | \theta_G) Pr(\theta_G)}{Pr(BR | \theta_G) Pr(GR | \theta_G) Pr(\theta_G) + Pr(BR | \theta_B) Pr(\theta_B)} \\ &= \frac{\mu_0 \alpha (1 - \alpha)}{\mu_0 \alpha (1 - \alpha) + (1 - \mu_0) \beta (1 - \beta)}, \end{aligned}$$

where $Pr(\theta_G) = \mu_0$, $Pr(\theta_B) = 1 - \mu_0$, $Pr(GR | \theta_G) = \alpha$, $Pr(BR | \theta_G) = 1 - \alpha$, $Pr(GR | \theta_B) = \beta$, $Pr(BR | \theta_B) = 1 - \beta$, and the reports are independent of each other, so $Pr(GR, BR | \theta) = Pr(GR | \theta) Pr(BR | \theta)$.

In general, let t_{GR} represent the number of positive feedback and t_{BR} be the number of negative feedback to the seller prior to the period t , so for $t = t_{GR} + t_{BR} + 1$, the buyer's belief of meeting

a good seller at period t is

$$\mu_{t-1} = \mu_{t_{GR}+t_{BR}} = \frac{\mu_0 \alpha^{t_{GR}} (1 - \alpha)^{t_{BR}}}{\mu_0 \alpha^{t_{GR}} (1 - \alpha)^{t_{BR}} + (1 - \mu_0) \beta^{t_{GR}} (1 - \beta)^{t_{BR}}}. \quad (2)$$

The seller's payoff at period t is

$$U_s = P = P(V_b(K)) = \mu_t \alpha + (1 - \mu_t) \beta, \quad (3)$$

and the buyer's payoff in period t is

$$U_b(P, NR/GR/BR) = 1 - P = 1 - (\mu_t \alpha + (1 - \mu_t) \beta) \quad (4)$$

if he received high quality transaction, and it is

$$U_b(P, NR/GR/BR) = -P = -(\mu_t \alpha + (1 - \mu_t) \beta) \quad (5)$$

if he received low quality transaction. As the game repeats, μ converges to 1 for good sellers, and converges to 0 for bad sellers; buyer's willingness to pay converges to α for good type sellers and converges to β for bad type sellers.

No reporting cost is the ideal situation, while in reality, there always exist some kind of cost associated with reporting. We will exam the case where it costs the same to provide positive and negative feedback and the case where the costs are different for positive and negative feedback in the following two subsections.

4.2.2 Case 2: Symmetric Reporting Cost ($C_{GR} = C_{BR} > 0$)

Secondly, let us examine the case where there is reporting costs on both positive feedback (GR) and negative feedback (BR). The reporting costs may be time or energy spent on writing reports, or the opportunity cost during that time, or the retaliation by the seller if the buyer leaves a bad report. For simplicity, we denote all the reporting costs in terms of dollars, and the highest reporting costs for the buyers is C .

Not reporting (NR) dominates reporting (GR and BR) for buyers, so there is no report about the seller's previous history and reputation. A buyer can not update her beliefs, so the buyer's willingness to pay is $P = P_1 = \mu_0 \alpha + (1 - \mu_0) \beta$ for every period t . In equilibrium, the buyers'

strategy is to choose to bid at P_1 and do not report feedback, i.e., $(P_i = P_1, NR)$, and the seller's strategy is to accept the bid if P_i is equal or greater than the seller's reservation price V_s . If we assume the reservation price is 0 for both types of sellers, sellers will always accept the bid. However, a good seller gets less than what she could get in the case of no reporting cost, and a bad seller gets more than what she could get in the case of no reporting cost in the long run. There is a wealth transfer from good sellers to bad sellers.

If good sellers' reservation price is higher than P_1 , then only a bad seller accepts the bid, so good sellers will be driven out of the market, buyers' willingness to pay will drop to $P_i = \beta$, and eBay's expected revenue will also drop. This is similar to Akerlof's (1997) lemon car market, as good quality cars are driven out by lemons because of asymmetric information of product quality. Here, good sellers are driven out by bad sellers due to the asymmetric information about the seller's types which determine the quality of the products. Another way to think about it is that if there are two online markets, and one has a reporting cost of 0, and another has a positive reporting cost, then good sellers will want to get the higher price, so they will move to the markets where there is no reporting cost. As a consequence, there is another separation of buyers. Those who want cheap things and do not care about low-quality transactions will stay in the market with reporting cost, and those who care about the quality of transactions will go to another market where there are many good sellers.

To see why it is also in eBay's (or other online auction sites') best interest to identify good sellers from bad sellers, we can consider the following argument. If the population of the seller is fixed at M , and eBay's revenue is an increasing function of sale value, then eBay's revenue is proportional to $\mu_0 M \alpha + (1 - \mu_0) M \beta$ when there is no reporting cost. If there is reporting cost and the good seller's reservation price is higher than P_1 , then the good sellers will not sell in this market, and only bad sellers stay in the market, so the buyers' willingness to pay will be β . If μ_0 of the M sellers are good sellers, and eBay's revenue is an increasing function of sale value, then eBay's revenue is proportional to $(1 - \mu_0) M \beta$, which is less than the earlier case.

In order to keep the good sellers whose reservation price is higher than P_1 in the market, we need to provide a means of increasing the buyers' willingness to pay to the good sellers. Therefore we need the reputation system to help to identify good sellers.

4.2.3 Asymmetric Reporting Cost ($C_{GR} \neq C_{BR} > 0$)

Third, let us see what will happen if buyers bear different cost for submitting good reports versus bad reports. Suppose there are three sellers in the market, and the Table 1 shows their ratings profiles on eBay.

Seller	Feedback			Total rating
	+1	0	-1	
<i>A</i>	18	18	27	-9
<i>B</i>	10	30	9	1
<i>C</i>	21	1	13	8

Table 1: Rankings of reputation profiles

Seller Ann has 18 positive, 18 neutral and 27 negative ratings, so her overall rating is -9 ; seller Bob has 10 positive, 30 neutral, and 9 negative ratings, so his overall rating is 1 (On eBay, the overall rating is the sum of all the positive, neutral, and positive ratings); and seller Cindy has 21 positive, 1 neutral and 13 positive ratings, so her overall rating is 8. If we can observe all the information about their ratings, then we can see seller Cindy has the highest overall rating, followed by Bob, and then Ann (i.e., $Cindy \succ Bob \succ Ann$). If there are reporting costs only on good reports, GR , then we will not observe GR s, and the overall ranking will reflect that Bob is a better seller than seller Cindy and Ann, respectively (i.e. $Bob \succ Cindy \succ Ann$). If there are reporting costs only on bad reports, BR , then the overall ranking will be $Cindy \succ Ann \succ Bob$. In fact, when we can observe all the information, the overall rating is consistent with the ranking by using a Borda Count voting rule. When we cannot observe GR s, the ranking is the same as using the anti-plurality voting rule. When we cannot observe BR s, the ranking is the same as using the plurality voting rule. Much research has shown that the Borda Count has the fewest problems among those voting rules (Saari and Sieberg (2001), Saari (1999), Saari (2001), Li (2006)). The best case is when we can observe all the reports and sum them up. Since traders only can observe the existing reports, they do not know the total number of transactions.

This example shows what can go wrong if we do not have complete information of traders' reputation. Using Bayesian updating, if buyers know that there are reporting costs, no matter if the cost is on good feedback (GR) or negative feedback (BR), they cannot correctly update their beliefs by using the information from rating profiles, thus their willingness to pay is still P_1 . In next section, we will propose a rebate incentive mechanism to the reputation system and examine the effect of this rebate option on improve current reputation systems.

5 Improvement of Current Reputation Systems in Online Auction Markets

In this section, we propose an improvement on current reputation systems in online auction markets. Namely, we propose that sellers be allowed to reward buyers who report the quality of transactions.

If there are reporting costs, previous theoretical results predict that no buyer wants that report. While in reality, many buyers will still report. It might be because altruism, community recognition, social norms, emotional expression, or that different buyers have different reporting costs (Bolton et al. (2003), Gazzale (2005), Xiao and Houser (2005), Resnick et al. (forthcoming)). However, as long as some of the buyers bear some reporting costs, the information about the sellers' reputation profile is incomplete. If the buyers use the incomplete information to make bidding decisions, they might bid higher or lower than what they should bid. It is important to have complete information of the sellers past history. We suggest to provide incentives for the buyer to report and make all the information available to everyone.

How might this be achieved? One way is to eliminate the reporting costs for the buyers. Will eBay want to compensate buyers for their reporting costs? It would seem prohibitively expensive, since even providing \$0.01 per transaction would be a huge cost for eBay due to the millions of daily transactions. What about sellers providing incentives to buyers? Will sellers want to compensate the buyers' reporting costs? What type of sellers would be willing to compensate this cost to the buyers? As we have seen, good sellers are more likely to sell the same product at a higher price if there are full reports. However, bad sellers are more likely to get lower prices if there are full reports available to consumers. Therefore, it appears that good sellers would be more inclined to provide a rebate than the bad sellers. If so, it seems that there exists a separating equilibrium which can help us identify the seller's type. Before we draw this conclusion, we need to analyze the equilibrium.

5.1 Model Setup

To see whether sellers want to provide incentives for buyers to report, we assume that all sellers can choose a rebate, r , which is greater or equal to C . The game played in every period is described as the following:

1. Nature chooses seller's type $\theta \in \{\theta_G, \theta_B\}$.

2. The seller chooses to rebate r or not, where $r > C$, the seller's actions set is $\{Rebate(R_S), NoRebate(NR_S)\}$.
3. Buyers choose a bid, at the expected value of the transaction, $P \geq 0$.
4. The seller chooses to accept or reject P based on his reservation price. If he rejects, the game ends. If he accepts, then the game moves onto the next step.²⁶
5. Nature chooses the quality of the transaction that buyers get from different types of sellers, Q_H or Q_L . Transaction quality is a new draw in every period.
 $q(\theta) =$ probability of providing Q_H .
 $q(\theta_G) = \alpha$
 $q(\theta_B) = \beta$
 $0 \leq \beta < \alpha \leq 1$
6. The buyer chooses (NR, GR, BR) . The buyer can choose to give a good report (GR), bad report (BR), or no report (NR); the reporting cost is C for all buyers. Assume all buyers report honestly if they decide to report, i.e. GR for Q_H and BR for Q_L .

7. These are payoffs received for period t .

$$U_s(Accept, R_S, \text{if buyer choose GR or BR}) = P - 0 - r = P - r;$$

$$U_s(Accept, R_S, \text{if buyer choose NR}) = P;$$

$$U_s(Accept, NR_S) = P - 0 = P;$$

$$U_s(Reject, R_S) = 0;$$

$$U_s(Reject, NR_S) = 0;$$

$$U_b(P, NR, \text{if } Q_H) = 1 - P;$$

$$U_b(P, NR, \text{if } Q_L) = -P;$$

$$U_b(P, GR, \text{if } Q_H \text{ and seller chooses } R_S) = 1 - P - C + r;$$

$$U_b(P, GR, \text{if } Q_H \text{ and seller chooses } NR_S) = 1 - P - C;$$

$$U_b(P, BR, \text{if } Q_L \text{ and seller chooses } R_S) = -P - C + r;$$

$$U_b(P, BR, \text{if } Q_L \text{ and seller chooses } NR_S) = -P - C;$$

To find possible equilibria, we use the guess and verify method to look for the Perfect Bayesian Equilibrium (PBE).

²⁶For simplicity, we assume the seller's reservation price is 0.

5.2 Separating Equilibrium

Proposition 5.1 *No separating equilibrium exists where good (bad) type sellers choose to provide feedback rebates and bad (good) type sellers choose not to do so.*

Proof: First, let's examine the separating equilibrium where good sellers choose rebate (R_S), and bad sellers choose no rebate (NR_S). If it is an equilibrium, then buyers can identify the seller's type by observing whether the seller chooses the rebate option. If the seller chooses it, then she is a good seller, the buyer's willingness to pay is $\alpha + r - C$, and the good seller's payoff $\alpha - C$. Since buyers bid for the product, and rebate on the report is more than the cost of the report, $r > C$, the winning bidder will take the rebate and reporting cost into account when he bids, otherwise the buyer can not win the bid. Since the winning bidder includes the rebate in the bidding price, he would choose to report after the transaction, otherwise he would lose the amount of rebate which he has paid in the bidding price. If a seller does not choose the rebate option, then she is a bad seller, the buyer's willingness to pay is β , and bad seller's payoff is β . If the reporting cost is larger than the price difference between good and bad sellers, i.e., $C > \alpha - \beta$, then both good and bad sellers choose not to rebate (NR_S). If the reporting cost is less than the price difference between good and bad sellers, i.e., $C \leq \alpha - \beta$, we need to check whether any sellers want to deviate from the separating equilibrium. A bad seller would get the higher payoff $\alpha - C$ instead of β if she pretends to be a good seller by choosing the rebate option. Thus, the separating equilibrium does not exist.

Another separating equilibrium where good sellers choose not to rebate (NR_S) and bad sellers choose rebate (R_S) does not exist either. The payoff to the good seller is α , and the payoff to the bad seller is $\beta - C$, and $\alpha > \beta$, so that the bad seller can have higher payoff if he presents to be a good seller by choosing rebate. The bad sellers have incentives to deviate from this separating equilibrium. Another way to check the existence of separating equilibrium is by checking the single-crossing property. Since there is no single-crossing property, i.e., the rebate costs the same for the both type sellers, there exists no separating equilibrium. \square

After we examine the separating equilibrium, the natural next step is to examine pooling equilibrium.

5.3 Pooling Equilibrium

Proposition 5.2 *If the reporting cost C is smaller than the expected loss of treating a bad seller as a good one, i.e., $(1 - \mu_0)(\alpha - \beta)$, there exists a pooling equilibrium where both types of sellers*

choose to provide rebates for reporting, and buyers learn a seller's type by observing the feedback reports. If the reporting cost C is greater than the expected loss of treating a bad seller as a good one, i.e., $(1 - \mu_0)(\alpha - \beta)$, then both types of sellers would choose no rebate, NR_S .

Proof: First, we examine the pooling equilibrium where both type sellers choose to provide rebates, R_S . In this case, buyers cannot update their beliefs by observing the sellers' choice of providing a rebate. Since both types of sellers provide rebates, all buyers will provide reports. The future buyer can, by using the information about seller's previous history, update her beliefs on the seller's type. If the buyer does not report, her willingness to pay at period $t + 1$ is

$$P_{t+1} = \mu_t \alpha + (1 - \mu_t) \beta, \quad (6)$$

while if she choose to report, her willingness to pay is

$$P_{t+1} = \mu_t \alpha + (1 - \mu_t) \beta - C + r. \quad (7)$$

The bidding price in period $t + 1$ is:

$$P_{t+1} = \mu_t \alpha + (1 - \mu_t) \beta + r - C. \quad (8)$$

The payoff for the seller at period t is:

$$U_s(\text{Accept}, R_S, \text{if buyer chooses } GR \text{ or } BR) = P - r = \mu_t \alpha + (1 - \mu_t) \beta - C. \quad (9)$$

It is less than the case of the benchmark model without the reporting cost in equation (3), and the reporting cost is transferred to the sellers.

If the transaction is high quality, the buyer's payoffs in period t is

$$\begin{aligned} U_b(P, GR, \text{if } Q_H \text{ and seller chooses } R_S) &= 1 - P - C + r \\ &= 1 - (\mu_t \alpha + (1 - \mu_t) \beta + r - C) - C + r \\ &= 1 - [\mu_t \alpha + (1 - \mu_t) \beta]. \end{aligned} \quad (10)$$

If the transaction is low quality, then it is

$$\begin{aligned}
U_b(P, BR, \text{if } Q_L \text{ and seller chooses } R_S) &= -P - C + r \\
&= -(\mu_t\alpha + (1 - \mu_t)\beta + r - C) - C + r \\
&= -[\mu_t\alpha + (1 - \mu_t)\beta].
\end{aligned} \tag{11}$$

They are the same as in the case of benchmark model without the reporting cost as in equation (4) and (5). Thus, sellers bear all the reporting cost if the incentive mechanism is adopted.

In the model of this section, we do not allow sellers to change their IDs. As the number of time periods t becomes infinite, μ for the good seller converges to 1, and the buyer's willingness to pay converges to α ; while μ for the bad seller converges to 0, and the buyer's willingness to pay converges to β . If the payoff from providing the rebate is higher than the payoff from not providing the rebate in the long run, i.e., $\alpha - C \geq P_1 = \mu_0\alpha + (1 - \mu_0)\beta$, then the good seller will choose to provide the rebate. If the payoff from providing the rebate is higher than the payoff from not providing at the beginning, i.e., $P_1 = \mu_0\alpha + (1 - \mu_0)\beta - C > \beta$, then the bad seller want to mimic good seller and choose the rebate until his payoff is less than P_1 (the price for a new seller), i.e., $P_t = \mu_t\alpha + (1 - \mu_0)\beta - C < P_1 = \mu_0\alpha + (1 - \mu_0)\beta - C$. So as long as $C \leq (1 - \mu_0)(\alpha - \beta)$ and $C < \mu_0(\alpha - \beta)$, the good sellers will choose to give the rebate, and the bad sellers will also give the rebate until their payoff $\mu_t\alpha + (1 - \mu_t)\beta - C$ is less than P_1 , and choose no rebate otherwise. If $C > (1 - \mu_0)(\alpha - \beta)$, both types of sellers want to choose no rebate, NR_S .

Another pooling equilibrium is that both types of sellers choose not to rebate, (NR_S) supported by the off-equilibrium path belief that anyone who chooses to rebate, R_S , must be a bad seller. In this case, the buyer's willingness to pay is the same for all the periods, $P_i = P_1 = \mu_0\alpha + (1 - \mu_0)\beta$. Seller's payoff is $P_1 = \mu_0\alpha + (1 - \mu_0)\beta$ for every period.

If $C \leq (1 - \mu_0)(\alpha - \beta)$, this equilibrium does not exist if we use the intuition criteria. Since the good sellers want to separate from the bad sellers, good sellers have an incentive to give rebates, thus making the buyers report. So the off-equilibrium belief where anyone that chooses rebate is bad is not feasible. If $\alpha - C < \mu_0\alpha + (1 - \mu_0)\beta$, then the pooling equilibrium in which both types of sellers choose no rebate, NR_S , exists. \square

Proposition 5.2 says that if the reporting cost is not too high relative to the difference between the buyers' willingness to pay to the good and bad sellers, then both types of sellers will provide the rebate option. If the reporting cost is too high, then no seller wants to provide the rebate.

For example, if a good seller sells a book which is worth \$10 in a bookstore, then the difference of willingness to pay to a good seller and to a bad seller may be just \$0.50. If the reporting cost is higher than \$0.50, then even the good seller does not want to give a rebate contingent on feedback. While if the product is a Dell computer worth \$1300 on Dell's web site, and the difference in willingness to pay to the different types of sellers is about \$200. The reporting cost of most people is certainly less than this amount, so that the good sellers want to provide the rebate as well as the bad sellers. In our model, we assume sellers list the same product in every period, so the decision of providing rebate depends on the relative cost of reporting.

5.4 Types of Rebate Mechanisms

Dellarocas et al. (2006) provide an in depth review of topics related to reputation mechanism design. They point out that the bilateral feedback mechanism adopted by eBay may cause an adverse effect because it allows for retaliation and reciprocation. Even after an unsatisfactory transaction, a buyer who values her own reputation may be reluctant to post a “negative” feedback (first) for fear that the seller might retaliate and leaves a negative feedback in response. Sellers could also use retaliation to build up a reputation of “being tough against negative feedback” to discourage future negative feedback when his performance is poor. Reciprocation compromises the effectiveness of feedback mechanisms by unfairly inflating the reputation of users because a buyer may feel obligated to return good feedback after she receives good feedback, even if the seller's performance was not terribly good. Also, a seller can choose to always reciprocate positive feedback in order to build a reputation of being a “reciprocator” who encourages future buyers to give positive feedback first. Dellarocas and Wood (2006) and Klein et al. (2005) provide strong empirical evidence to support this claim.

If the reason for buyers not to leave negative feedback is fear of retaliation, one possible type of rebate mechanism is that sellers commit to set up an automatic feedback contingent on receiving payment. In this system, they can leave feedback contingent on receiving payments, such that the sellers cannot retaliate against the buyers afterwards. Another type of rebate mechanism is a combination of the automatic feedback leaving option together with monetary incentives. For example, a seller can set up an option to automatically leave feedback contingent on receiving payment and automatically give monetary incentives to buyers contingent on receiving feedback, regardless of whether it is positive or negative feedback. With advanced IT technology, the market maker (e.g., eBay) can provide the rebate mechanism options to at very low cost. Buyers can

observe whether a seller chooses these options and then decide whether to bid and how much to bid.

6 Extensions

In this section, we discuss possible extensions of the rebate incentive mechanism. The first one deals with the ID-changing issue. Since sellers can easily change their online identities in online auction markets, we look for possible conditions that can discourage sellers to do so. The second extension introduces moral hazard into the reputation model, and we show that the rebate incentive mechanism can induce bad sellers to behave cooperatively.

6.1 Changing IDs

In the case where $C < (1 - \mu_0)(\alpha - \beta)$, good sellers always choose the rebate, and bad sellers choose the rebate until their payoff is less than β . If we allow sellers to change identities and start over as new sellers, then bad sellers will change their IDs and offer rebates if their future expected price minus reporting cost is less than β . Suppose in period T , the bad type seller will get $P_T = \mu_{T-1}\alpha + (1 - \mu_{T-1})\beta$, and his payoff is $U_s = \mu_{T-1}\alpha + (1 - \mu_{T-1})\beta - C > \beta$.

Proposition 6.1 *If the cost of changing an ID is higher than $\frac{\mu_0^2(1-\mu_0)(\alpha-\beta)^3}{[\mu_0\alpha+(1-\mu_0)\beta][\mu_0(1-\alpha)+(1-\mu_0)(1-\beta)]}$, then no seller will change her ID.*

Proof: With probability β , a bad type seller provides a high quality, Q_H , in period 1, and he gets a good report, GR . The buyer's belief on his type in the second period is

$$\mu_1 = \frac{\mu_0\alpha}{\mu_0\alpha + (1 - \mu_0)\beta}.$$

With probability $1 - \beta$, the bad seller provides a low quality transaction, Q_L , in period 1, and he gets a bad report, BR . The buyer's belief on his type in the second period is

$$\mu_1 = \frac{\mu_0(1 - \alpha)}{\mu_0(1 - \alpha) + (1 - \mu_0)(1 - \beta)}.$$

Since buyer's willingness to pay is $P_{t+1} = \mu_t\alpha + (1 - \mu_t)\beta$. The bad seller's expected payoff at period 2 is

$$\begin{aligned}
E(P_2) &= E(\mu_2\alpha + (1 - \mu_2)\beta) - C \\
&= \alpha E(\mu_2) + \beta(1 - E(\mu_2)) - C \\
&= \alpha \left[\frac{\beta\mu_0\alpha}{\mu_0\alpha + (1 - \mu_0)\beta} + \frac{(1 - \beta)\mu_0(1 - \alpha)}{\mu_0(1 - \alpha) + (1 - \mu_0)(1 - \beta)} \right] + \\
&\quad \beta \left[1 - \left(\frac{\beta\mu_0\alpha}{\mu_0\alpha + (1 - \mu_0)\beta} + \frac{(1 - \beta)\mu_0(1 - \alpha)}{\mu_0(1 - \alpha) + (1 - \mu_0)(1 - \beta)} \right) \right] - C.
\end{aligned}$$

If she is free to change her ID, the bad seller can start as a new seller, and she will get $P_1 = \mu_0\alpha + (1 - \mu_0)\beta - C$ in the second period.

To see whether the bad type seller can be better off by changing her ID, we can do the following calculation, which compares expected future payoff with a new ID and with the old ID:

$$\begin{aligned}
E(P_2) - P_1 &= (\alpha - \beta) \left[\frac{\beta\mu_0\alpha}{\mu_0\alpha + (1 - \mu_0)\beta} \right. \\
&\quad \left. + \frac{(1 - \beta)\mu_0(1 - \alpha)}{\mu_0(1 - \alpha) + (1 - \mu_0)(1 - \beta)} - \mu_0 \right] \\
&= \frac{(\alpha - \beta) [-\mu_0^2(1 - \mu_0)(\alpha - \beta)^2]}{[\mu_0\alpha + (1 - \mu_0)\beta][\mu_0(1 - \alpha) + (1 - \mu_0)(1 - \beta)]} \\
&= \frac{-\mu_0^2(1 - \mu_0)(\alpha - \beta)^3}{[\mu_0\alpha + (1 - \mu_0)\beta][\mu_0(1 - \alpha) + (1 - \mu_0)(1 - \beta)]}.
\end{aligned}$$

Since $\alpha > \beta$ and $0 < \mu < 1$, it is clear to see that $E(P_2) < P_1$ for bad sellers. Thus, the expected price in the second period is less than what the seller can get if she changes her ID and starts over as a new seller. Bad sellers can change their IDs whenever their next period payoffs are less than P_1 .

In order to discourage bad sellers from changing their IDs, the online market can impose a cost for ID-changing, k , and it is a entry cost for all new users (or the users who change their IDs) of the online market, for example, providing the user's bank account information. If the bad seller does not change ID, her expected payoff in period 2 is $E(P_2)$, and her total expected payoff over the two periods is $P_1 + \delta E(P_2)$. If she changes ID, she needs to pay k , and the bad seller's total payoff over the two period is $P_1 + \delta(P_1 - k)$. If $P_1 + \delta(P_1 - k) \leq P_1 + \delta E(P_2)$, then the bad seller will not change ID. In other words, in order to prevent bad sellers from changing their IDs, we need to set the cost of ID changing significantly high enough, $k \geq \frac{\mu_0^2(1 - \mu_0)(\alpha - \beta)^3}{[\mu_0\alpha + (1 - \mu_0)\beta][\mu_0(1 - \alpha) + (1 - \mu_0)(1 - \beta)]}$, to

discourage the sellers from changing IDs.

Let us take a look at the good sellers. The good sellers will get $P_1 = \mu_0\alpha + (1 - \mu_0)\beta$ in period 1. With probability α , a good seller provides a high quality transaction, Q_H , in period 1, and she gets a good report, GR . The buyer's belief of his type in the second period is

$$\mu_1 = \frac{\mu_0\alpha}{\mu_0\alpha + (1 - \mu_0)\beta}.$$

With probability $1 - \alpha$, a good seller provides a low quality transaction, Q_L , in period 1, and he gets a bad report, BR . The buyer's belief on his type in the second period is

$$\mu_1 = \frac{\mu_0(1 - \alpha)}{\mu_0(1 - \alpha) + (1 - \mu_0)(1 - \beta)}.$$

Since the buyer's willingness to pay is $P_{t+1} = \mu_t\alpha + (1 - \mu_t)\beta$, the good seller's expected payoff is

$$\begin{aligned} E(P_2) &= E(\mu_2\alpha + (1 - \mu_2)\beta) - C \\ &= \alpha E(\mu_2) + \beta(1 - E(\mu_2)) - C \\ &= \alpha \left[\frac{\alpha\mu_0\alpha}{\mu_0\alpha + (1 - \mu_0)\beta} + \frac{(1 - \alpha)\mu_0(1 - \alpha)}{\mu_0(1 - \alpha) + (1 - \mu_0)(1 - \beta)} \right] + \\ &\quad \beta \left[1 - \left(\frac{\alpha\mu_0\alpha}{\mu_0\alpha + (1 - \mu_0)\beta} + \frac{(1 - \alpha)\mu_0(1 - \alpha)}{\mu_0(1 - \alpha) + (1 - \mu_0)(1 - \beta)} \right) \right] - C. \end{aligned}$$

If she is free to change ID, the good seller can start as a new seller and get $P_1 = \mu_0\alpha + (1 - \mu_0)\beta - C$ in the second period. To see whether a good seller would want to change her ID, we need to compare $E(P_2)$ with P_1 :

$$\begin{aligned} E(P_2) - P_1 &= \alpha \left[\frac{\alpha\mu_0\alpha}{\mu_0\alpha + (1 - \mu_0)\beta} + \frac{(1 - \alpha)\mu_0(1 - \alpha)}{\mu_0(1 - \alpha) + (1 - \mu_0)(1 - \beta)} \right] + \\ &\quad \beta \left[1 - \left(\frac{\alpha\mu_0\alpha}{\mu_0\alpha + (1 - \mu_0)\beta} + \frac{(1 - \alpha)\mu_0(1 - \alpha)}{\mu_0(1 - \alpha) + (1 - \mu_0)(1 - \beta)} \right) \right] \\ &\quad - [\mu_0\alpha + (1 - \mu_0)\beta] \\ &= (\alpha - \beta) \left[\frac{\alpha\mu_0\alpha}{\mu_0\alpha + (1 - \mu_0)\beta} + \frac{(1 - \alpha)\mu_0(1 - \alpha)}{\mu_0(1 - \alpha) + (1 - \mu_0)(1 - \beta)} - \mu_0 \right] \\ &= (\alpha - \beta)\mu_0 \left[\frac{\alpha^2}{\mu_0\alpha + (1 - \mu_0)\beta} + \frac{(1 - \alpha)^2}{\mu_0(1 - \alpha) + (1 - \mu_0)(1 - \beta)} - 1 \right] \\ &= \frac{\mu_0(1 - \mu_0)^2(\alpha - \beta)^3}{[\mu_0\alpha + (1 - \mu_0)\beta][\mu_0(1 - \alpha) + (1 - \mu_0)(1 - \beta)]}. \end{aligned}$$

Since $\alpha > \beta$ and $0 < \mu < 1$, it is clear that $E(P_2) \geq P_1$ for a good seller, so the good seller does not have an incentive to change her ID. \square

The possible forms of ID-changing cost can be a fee is charged when someone wants to become a seller, or the verification of the bank account of a seller.

6.2 Model of Adverse Selection and Moral Hazard

In the benchmark model of adverse selection, the transaction outcomes are chosen by nature and not by the sellers. In reality, we often see that the sellers' actions have an impact on the transaction outcomes. If the sellers put more effort into packaging and shipping the product, the transaction outcomes are more likely to be good. In order to model the sellers' effort in the model, we now explore a model with both adverse selection and moral hazard.

Suppose there are two types of sellers, good type (G) and bad type (B). If both types of sellers put forth effort ($e = 1$), they will provide high quality products (Q_H) with probability 1.²⁷ If they do not put forth an effort ($e = 0$), then they will provide a low quality product (Q_L) with probability 1. Assume good sellers' cost of making an effort is 0, $C_{\theta_G}(e = 1) = e(0) = 0$, and bad sellers' cost of making an effort is $C_{\theta_B}(e = 1) = e(1) > 0$. To simplify, we assume good sellers always make effort, because it costs nothing to them.

The game played in every period is described as the following:

1. Nature chooses sellers type $\theta \in \{\theta_G, \theta_B\}$, and the prior of meeting a θ_G seller is μ_0 .
2. Buyers choose a bid, $P \geq 0$.
3. The seller chooses to accept or reject P based on his reservation price. If he rejects, the game ends. If he accepts, then go to next step.²⁸
4. The seller chooses to put forth an effort or not, $e = 1$ or $e = 0$.
5. Buyers can choose to give good report (GR), bad report (BR), or no report (NR); the reporting cost is C for all buyers. Assume all the buyers report honestly if they decide to report, i.e. GR for Q_H and BG for Q_L .
6. The following are the Payoffs received for period t .

$$U_s(\theta_G, e = 1) = P;$$

²⁷We can assume this probability to be α , and the general result still holds.

²⁸For simplicity, we assume the seller's reservation price is 0.

$$\begin{aligned}
U_s(\theta_G, e = 0) &= P; \\
U_s(\theta_B, e = 1) &= P - e(1); \\
U_s(\theta_B, e = 0) &= P; \\
U_b(P; NR, \text{if } Q_H) &= 1 - P; \\
U_b(P; NR, \text{if } Q_L) &= -P; \\
U_b(P; GR, \text{if } Q_H) &= 1 - P - C; \\
U_b(P; BR, \text{if } Q_L) &= -P - C.
\end{aligned}$$

If there is no reporting cost, $C = 0$, all buyers report. When a bad seller does not make an effort, he will get a bad report, BR . If the game repeats T periods, a bad seller will not make an effort in the last period.

Buyers willingness to pay is $P_{t+1} = \mu_t + (1 - \mu_t)\hat{e}_t$, where \hat{e}_t is the buyer's expectation of the seller's effort. The belief that the seller is good type in period 2 is

$$\begin{aligned}
\mu_1 &= P(\theta_G|GR) = \frac{P(GR|\theta_G)P(\theta_G)}{P(GR|\theta_G)P(\theta_G) + P(GR|\theta_B)P(\theta_B)} \\
&= \frac{\mu_0}{\mu_0 + (1 - \mu_0)P(e_1 = 1|\theta_B)} \\
&= \frac{\mu_0}{\mu_0 + (1 - \mu_0)e(1)}.
\end{aligned}$$

In period t , the updated prior of meeting a good seller is:

$$\mu_{t-1} = \frac{\mu_{t-2}}{\mu_{t-2} + (1 - \mu_{t-2})e_{t-1}}.$$

In the last period, T , the buyer's willingness to pay is μ_T .

If $T = 2$, the seller's strategy can be $(e(0), e(0))$ or $(e(1), e(0))$, where the first element represents the action in period $t = 1$, and the second represents the action in period $t = 2$. To examine which strategy is right for the seller, we need to calculate the payoffs.

If the bad seller chooses $(e(0), e(0))$, his total payoff over the two periods is $U_s = \mu_0$. If he chooses $(e(1), e(0))$, his total payoff is

$$\begin{aligned}
U_s &= P_1 - e(1) + \delta P_2 \\
&= (\mu_0 + (1 - \mu_0)\hat{e}_1 - e(1) + \delta \frac{\mu_0}{\mu_0 + (1 - \mu_0)\hat{e}_1}) \\
&= 1 - e(1) + \delta \mu_0.
\end{aligned}$$

If $1 - e(1) + \delta\mu_0 > \mu_0$ (i.e., $e(1) < 1 - (1 - \delta)\mu_0$), then the bad seller's best strategy is to make an effort in the first period but not in the second period, $(e(1), e(0))$.

For a T -period game, the payoffs to bad type sellers in each period are the following:

At $t = 1$, $V_1 = P_1 + \delta I(e_1)V_2 - e_1(1)$

If $e_1 = 1$, $I(e_1) = 1$, and $V_1 = 1 + \delta V_2 - e(1)$.

If $e_1 = 0$, $I(e_1) = 0$, and $V_1 = P_1 = \mu_0 + (1 - \mu_0)\hat{e}_1 = \mu_0$

At $t = 2$, $V_2 = P_2 + \delta I(e_2)V_3 - e_2(1)$

If $e_2 = 1$, $I(e_2) = 1$, and $V_2 = 1 + \delta V_3 - e(1)$.

If $e_2 = 0$, $I(e_2) = 0$, and $V_2 = P_2 = \mu_1 + (1 - \mu_1)\hat{e}_2 = \mu_1 = \mu_0$

....

At $t = T - 1$, $V_{T-1} = P_{T-1} + \delta I(e_{T-1})V_T - e_{T-1}(1)$

If $e_{T-1} = 1$, $I(e_{T-1}) = 1$, and $V_{T-1} = 1 + \delta V_T - e(1)$.

If $e_{T-1} = 0$, $I(e_{T-1}) = 0$, and $V_{T-1} = P_{T-1} = \mu_0$

At $t = T$, $V_T = P_T = \mu_{T-1} = \mu_0$.

In order to induce the bad type sellers to choose $e_t = 1$ for every period prior to T , the condition $e(1) < 1 - (1 - \delta)\mu_0$ has to be satisfied. That is, as long as $e(1) < 1 - (1 - \delta)\mu_0$, bad sellers will make genuine an effort for $t = 0$ to $t = T - 1$, but will cease to do so in the last period.

Proposition 6.2 *If the reporting cost C is less than $P_{T-1} + \delta I(e_{T-1})V_T - e_{T-1}(1) - \mu_0$ and $e(1) < 1 - (1 - \delta)\mu_0$, then a bad seller will choose the rebate option and put in effort in the first $T - 1$ periods and not put in effort in the last period T .*

Proof: If there are reporting costs, then no buyer will be inclined to report. In this case, the buyer's willingness to pay is $P_i = \mu_0$. The good sellers will be worse off than the case where there is no reporting cost, and the bad sellers will not make an effort in any period. If we use the incentive mechanism proposed in the pure adverse selection model, both types of sellers will choose to give a rebate if the reporting cost is less than the price difference for good transaction and bad transaction, i.e., $C < P_{T-1} + \delta I(e_{T-1})V_T - e_{T-1}(1) - \mu_0$, and bad sellers would put forth effort as long as their payoffs are more than μ_0 for each period. \square

Thus, the incentive mechanism can help induce bad sellers to cooperate. In that, it helps to sustain a trustful trading environment. Using the rebate together with the reputation system, the online market is self-sustainable, thus reducing the cost to the market designer.

7 Conclusion

According to Pew Internet & American Life Project's 2006 survey, the percentage of American adults using the Internet has grown from 46% in 2000 to 73% in 2005. That currently represents about 147 million people. About 67% of Internet users have purchased something online and 17% of them have sold something online. On a typical day, 6% of Internet users buy products online and 2% of them sell something online. The trend shows that more people are adopting online trading.²⁹ A trustworthy trading environment is essential to the success of online markets. In current online markets, buyers lack of incentive to report on the quality of sellers. Along with this problem, there is also the issue of buyers being reluctant to report negative feedback for fear of retaliation by sellers. These two conditions help create an environment where buyers are reluctant to report feedback that leaves subsequent buyers with a lack of adequate information about sellers, thus allowing bad sellers to commit fraud more freely. With the advent of the Web, online markets are much more dynamic than conventional markets. A new idea may create a giant in online markets. eBay, the largest online auction site in the U.S., is losing market share to Taobao in China.³⁰ To gain consumers' confidence in the online market, companies like eBay need to have an edge on fighting fraud and create a cooperative trading environment.

In this paper, we show that giving sellers the option to compensate buyers for their reporting costs could lead to a pooling equilibrium where both types of sellers choose to compensate buyers. Since feedback reveals information about the past history of sellers, this mechanism helps buyers learn the type of a seller in the pure adverse selection setting. The rebate mechanism induces bad sellers to raise the quality of their product and service in the model that combines adverse selection and moral hazard. As a result, good sellers would be compelled to participate in this market instead of leaving, and incentivize bad sellers to either leave the market or produce high quality transaction in the market.

This rebate mechanism can also be used for other online markets, such as online retail markets (i.e., Resellersrating.com and Pricegrabber.com) or price comparison sites (i.e., Shoppers.com, Kelkoo.com, and Nextag.com). Since there are many sellers in these online markets, and the rating

²⁹ Accessed from <http://www.pewinternet.org/trends.asp> on August 31, 2006.

³⁰ A study released earlier in May 2006 by the China Internet Network Information Center (CNNIC) confirms Taobao's claims to market dominance in China. The study, based on telephone and online surveys of buyers and sellers in Beijing, Shanghai, and Guangzhou, estimates Taobao's market share at 67.3 percent compared with eBay's 29.1 percent. Yahoo's interests are tied with Alibaba.com, China's leading online business-to-business platform, which owns auction site Taobao.com. In August 2005, Yahoo paid \$1 billion in cash for a 40 percent stake in Alibaba as part of a \$4-billion deal that gave Alibaba control over Yahoo's operations in China.

of each seller will affect the probability of sale, sellers could use a rebate option to induce more consumers to leave feedback. The difference between online retail markets and auction markets is that the feedback is bilateral in an auction market (i.e., the sellers can use their feedback about the buyers as a way of retaliation). Thus, one type of rebate mechanism is one in which sellers set up an automatic feedback contingent on receiving payment. Another potential type of rebate mechanism is a combination of the automatic feedback leaving option together with monetary incentives. For those in an online retailer market, monetary incentives or community recognition may be better type of a rebate mechanism. Extensions of this paper include modeling the timing decision of traders in bilateral feedback system and examining the effect on market efficiency by requiring all sellers leave feedback first. Another extension of this paper is to conduct experiments and test whether buyers' and sellers' behavior will change as theory predicts. Online markets provide natural labs for observing people's behavior and decisions. If we know how people react to different incentive mechanisms, it will be valuable for policy makers in the fields such as management, voting, and marketing.

A The changes eBay made after the introduction of feedback system

1. In 1999, eBay moved away from non-transaction based feedback by preventing members from leaving negative non-transactional feedback. By March 2000, all feedback became transaction based.

2. On June 16th, 2001, eBay introduced buyer/seller labels on the Member Profile page, which helped people distinguish the context in which a member had received feedback.

3. In January 2003, eBay introduced the Seller Information Box on the item page. This snapshot view of a seller contains information about the seller's feedback score and positive feedback percentage.

5. Also in 2003, eBay introduced an additional page that members with feedback scores of 10 or less have to read prior to leaving a neutral or negative feedback comment in order to make sure members understand the impact of leaving negative or neutral feedback.

6. On March 1st, 2003, eBay began reporting "Percentage of Positive," which is the ratio of positives received by the seller in her entire ebay history and "Seller's Age," which is the date when the trader registered on eBay.

7. On Feb 9th, 2004, eBay modified the Feedback Removal policy to provide members the ability to mutually withdraw feedback.

8. From September 20th, 2005, eBay removed feedback left by users who are indefinitely suspended within 90 days of registration.

9. In late 2005, eBay added two more changes. One was neutralizing feedback left by members who do not participate in the issue resolution processes, and another requiring new members to complete a tutorial before leaving neutral or negative feedback.

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