Money Talks: Rebate Mechanisms in Reputation System Design

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Abstract:
Reputation systems that rely on voluntary feedback from traders are important in creating and sustaining trust in markets. Reporting feedback, however, is often costly for the reporter and feedback is a public good. We combine theory with a laboratory experiment to study the effect of a novel seller precommitment mechanism on promoting feedback and market efficiency. Specifically, our precommitment mechanism provides sellers an option to commit by providing a rebate to reduce the buyer's feedback reporting cost before making purchasing decisions. Our theory predicts that this mechanism induces noncooperative sellers to cooperate in the market. Using a buyer-seller trust game with a unilateral feedback scheme, we find that the seller’s rebate decision has a significant impact on the buyer's purchasing decision via signaling the seller's cooperative type. Importantly, both theory and experiment find that this precommitment mechanism can significantly improve market efficiency.

JEL: C91, D82, L86, H41.

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I. Introduction

Asymmetric information is a common problem in exchange environments. The online market is a typical example. With the easy accessibility of the Internet, people all over the world are integrating their off-line life with online communities and markets. To use e-commerce as an example, US online retail (excluding auto, travel, and prescription drugs) managed to grow 11% in 2009 to reach $155.2 billion and occupied 6% of total US retail sales.1 Meanwhile, in China, with less than 25% Internet penetration rate, online retail sales increased by 93.7% and reached near 250 billion Renminbi in 2009. In Great Britain and France, the revenue from e-commerce was expected to increase by 17% and 24%, respectively.2 One important feature of online markets is that traders are usually anonymous and geographically dispersed. Participants in online market, thus, often have limited information about their trading partners or products. Efficient exchanges in such markets where information is asymmetric must consistently rely on trust among traders. Reputation systems as information aggregation devices have been designed to establish and sustain trust.3

A commonly adopted mechanism to build a reputation system is to rely on voluntary feedback from involved parties. For example, eBay and Amazon provide feedback systems that allow traders to obtain reputation information for their counterparties or the products on sale. Such reputation systems, however, may not be reliable. For example, only about 50% of buyers leave feedback after transactions on eBay. Furthermore, the existing feedback is biased toward the positive due to missing negative feedback (see Resnick and Zeckhauser, 2002, Cabral and Hortacsu, 2010,  

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3 See Bajari and Hortacsu, 2004; Bolton and Ockenfels, forthcoming; Bolton et al., 2005; Brandts and Figueras, 2003; Brown and Morgan, 2006; Dellarocas, 2003a; Diamond, 1989; Fehr et al., 2009; Friedman and Resnick, 2001; Grosskopf and Sarin, forthcoming; Houser and Wooders, 2006; Jin and Kato, 2006; Klein, 1997; Kreps and Wilson, 1982; Milgrom et al., 1990; Sobel, forthcoming; Shapiro, 1983; Resnick et al., 2006; Yamagishi and Matsuda, 2002; and Sobel, 2006.
and Dellarocas and Wood, 2008). The unreliability of a reputation system due to missing or biased information may limit the market’s growth.4

There are two possible explanations why the feedback system may be unreliable. First, there is a direct cost associated with reporting feedback. Participants must take time and effort to leave feedback. Once feedback is provided, it often becomes public information that everyone can access. It may not directly benefit those who leave feedback. Thus, the feedback system suffers the free-rider problem prevalent in public goods provision (see Avery et al., 1999, Bolton et al., 2004, and Chen et al., 2010).

Second, the missing feedback may also be attributed to the indirect cost of reporting caused by the design of the feedback system itself (see Dellarocas and Wood, 2008, Bolton et al., 2009 and Li, 2010b). For example, if both a buyer and a seller can leave feedback for each other after a transaction, the buyer may hesitate to leave negative feedback for fear of seller retaliations (e.g., Masclet and Pénard, 2008; Bolton et al., 2009). Some online markets, such as eBay, have realized the “fear of retaliation” problem; eBay even implemented a policy to ban sellers from leaving negative feedback for buyers in May 2008. Nevertheless, this type of mandatory policy has induced some sellers to switch to other sites and has discouraged sellers from leaving any feedback to buyers (Li, 2010a).

Various solutions have been proposed to promote contribution in feedback systems. For example, Ba et al. (2003) suggest a trusted third party (TTP) mechanism to issue certificates to sellers and buyers. Dellarocas (2003b) proposes charging a listing fee contingent on a seller's announced expected quality, rewarding the seller based on both the announced quality and the rating posted for that seller by the winning bidder for that listing. Both papers suggest monitoring systems to induce sellers to cooperate. Miller et al. (2005) and Jurca and Faltings (2007) propose truth-elicit ing incentive schemes to induce buyers to report honestly. Nevertheless, all these mechanisms either require buyers to bear the reporting cost or require the

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4 See Li (2010a) sections 3.2.2 and 3.2.3 for more discussion.
market (e.g., eBay) to provide incentives. If the reporting cost remains on the buyer’s side, buyers might still lack incentives to leave feedback. If the market provides such incentives, it may burden itself because of a huge volume of transactions.\(^5\)

In this paper, we propose and examine a precommitment mechanism in a listed-price market (that is, the price of the product is predetermined and fixed) that facilitates exchanges and improves market efficiency without requiring buyers or the market to bear the cost.\(^6\) In particular, the precommitment device takes the form of a monetary rebate option: sellers have the option to commit by providing a rebate to reduce the buyer’s reporting cost before the buyer decides whether to purchase, regardless whether the feedback is positive or negative. This precommitment mechanism plays a dual role of *incentivizing buyers to leave feedback* and *providing a device for sellers to signal quality or effort to cooperate*. Thus, it not only improves the reputation system, but also—and perhaps even more importantly—leads the sellers to cooperate voluntarily through the precommitment device.

We examine this precommitment mechanism both theoretically and experimentally in a unilateral feedback system where only buyers can leave feedback to sellers.\(^7\) We first demonstrate theoretically that under this mechanism, both good and bad sellers commit to provide a rebate and bad sellers *choose* to cooperate voluntarily. Consequently, the rebate mechanism promotes efficient trades. To test the hypothesis derived from the theory and provide empirical evidence for the effectiveness of the mechanism, we conduct experiments based on a buyer-seller trust

\(^5\) In addition to these incentive mechanisms, scholars have also investigated nonmonetary factors that influence the feedback reporting decisions. For example, Chen et al. (2010) run a field experiment on MovieLens.org and find that effective personalized social information can increase the level of public goods provision. Using data collected from Yelp.com, Wang (2010) finds that social image and reviewers’ productivities are positively correlated.

\(^6\) Li (2010a) provides a theoretical work on how a rebate mechanism works in an online auction market. In this paper, we build a model of listed-price markets that are more common than online auction markets and allow heterogeneous beliefs in the model.

\(^7\) As a first step, we choose a unilateral feedback system because it eliminates the concern of retaliation and provides clean evidences on the effects of (monetary) rebates and different reporting costs.
game modified from Bolton et al. (2004). In the game, a buyer first decides whether to buy a product from a seller. If the buyer decides to buy the product, the seller then decides whether to ship it. Our experiment consists of four treatments. In the baseline treatment, the computer automatically and truthfully records the feedback for each seller. In two other treatments, the feedback is reported by buyers at their own (monetary) cost which vary only in the magnitude of the reporting cost. The fourth treatment introduces the rebate mechanism under the higher reporting cost.

We find that both the reporting cost and the seller’s rebate decision have a significant effect on the buyer’s propensity to leave feedback when the seller cooperates, but not when the seller defects. This is consistent with previous findings that there exists an asymmetry in positive and negative reciprocity. We also find that a seller’s rebate decision affects the buyer’s propensity to report but not the honesty of the feedback. More importantly, we find that sellers’ rebate decisions affect buyers’ purchasing decisions by signaling the buyer about the sellers’ cooperative type rather than via compensating the ex post reporting cost. Consistent with the signal, the more rebates a seller provides, the more likely he will cooperate. Under the rebate mechanism, market efficiency increases with the frequency of rebates received by the buyers.

This paper contributes to both the mechanism design and the experimental economics literature on how to solve asymmetric information problems. First, from a mechanism designer’s perspective, rather than “forcing” cooperation, the precommitment mechanism introduces the idea of promoting voluntary cooperation in markets characterized by asymmetric information. By providing a precommitment option to the sellers, it allows both good sellers and bad sellers to coexist in the market, but it makes it possible for buyers to distinguish between them through feedback over time. Therefore, it improves market efficiency without driving out

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8 Gazzale and Khopkar (2008) also modified Bolton et al. (2004) to test whether allowing buyers to develop reputations for “information sharing” can increase trust and trustworthiness.
9 See Abeler et al., 2010; Al-Ubaydli and Lee, 2009; Gazzale and Khopkar, 2008; Keysar et al., 2008; Offerman, 2002.
some sellers through mandatory policies, such as eBay’s May 2008 policy change. Additionally, it internalizes the report costs between buyers and sellers without requiring the market to bear them. Second, from an empirical perspective, this paper provides experimental evidence that highlights the effectiveness of applying a precommitment device to promote cooperation. Our experiment data shows that the rebate mechanism can increase market efficiency as our theoretical model predicts.

The remainder of the paper is organized as follows: Section II introduces the theoretical framework of the rebate mechanism. Section III presents the experimental design. Theoretical predictions and hypotheses are presented in Section IV. Section V reports the results. Section VI concludes.

II. The Rebate Mechanism

In this section, we derive theoretical predictions of the outcomes under the precommitment mechanism in a listed-price market environment. In this paper, the precommitment option takes the form of a monetary rebate offer. Consider a market with $M$ sellers and $N$ buyers where sellers list the same good ($g$) in each period. For each period, a buyer is randomly matched with a seller and decides whether to buy the product. Suppose $M$ and $N$ are large, so a buyer will not meet the same seller again.\textsuperscript{10} If the buyer decides to buy, the seller then decides whether to cooperate. For the seller, to cooperate in this context means to provide a high quality transaction: he will ship the good to the buyer on time and the quality of the good is the same as he promised.

For simplicity reason, in the rest of the paper, we consider the seller as cooperative when he provides a high quality transaction by shipping the product.

Suppose a buyer values the product at $V_b$, a seller’s cost of the product is $V_s$, and the market price of the product is set at $P$ where $V_s < P < V_b$. The utilities for buyer and seller are as follows:\textsuperscript{11}

$$U_b(\text{buyer doesn't buy}) = U_s (\text{buyer doesn't buy}) = 0;$$

\textsuperscript{10} Resnick and Zeckhauser (2002) report that 89% of all buyer-seller pairs conducted just one transaction during the five-month period covered by their data set.

\textsuperscript{11} In this model, the “utility” equals “surplus.”
\[ U_b(\text{buyer buys, seller ships}) = V_b - P; \quad U_s(\text{buyer buys, seller ships}) = P - V_s; \]
\[ U_b(\text{buyer buys, seller doesn't ship}) = -P; \quad U_s(\text{buyer buys, seller doesn't ship}) = P. \]

There are two kinds of models in the literature of asymmetric information: the adverse selection model and the moral hazard model. In the former, an agent’s type is unobserved and his behavior depends on his type; in the latter, an agent’s action is unobserved and he decides which action to take. We provide a pure adverse selection model in the Appendix C.\(^\text{12}\) Here we consider a mixed model with both adverse selection and moral hazard with finite \(T\) periods. In the model, whether a seller ships is determined by nature according to his type, but he can take unobserved actions to affect the quality of transaction outcomes (to ship or not to ship the product in this case). Suppose there exist two types of sellers: a good type \(\theta_g\), who has a high probability \(\alpha\) of shipping by nature, and a bad type \(\theta_b\), who has a lower probability \(\beta\) of doing so, where \(0 \leq \beta \leq \alpha \leq 1\). Suppose also that sellers behave according to their types. For simplicity, we assume that \(V_s = 0\) for both types of sellers, and \(V_b = 1\) for buyers. Assume that both buyers and sellers are risk neutral, and \(\beta < P < \alpha\). In other words, if buyers can identify sellers’ types, they will buy from good sellers, but not from bad sellers.

We consider that buyers may have different experiences or beliefs in online shopping; for example, optimistic buyers may believe that most online sellers are good and pessimistic buyers may believe the opposite. We assume that buyer \(i\) has the initial belief that the proportion of good sellers in the market is \(\mu_0^i\), and the proportion of bad sellers is \(1 - \mu_0^i\). When there is no information about the seller’s past history, buyer \(i\)’s expected payoff is
\[ EU_{b0}^i = \mu_0^i \left( \alpha(1 - P) + (1 - \alpha)(-P) \right) + (1 - \mu_0^i) \left( \beta(1 - P) + (1 - \beta)(-P) \right) \]
\[ = \mu_0^i \alpha + \left(1 - \mu_0^i\right) \beta - P. \]

\(^{12}\) Our data from the survey also suggest that this is the case. For example, one of the participating sellers wrote on the post-experiment survey that he had made up her mind to cheat in the fourth and eighth rounds before he played the game, so his behavior is consistent with the pure adverse selection model.
If buyer \( i \)'s willingness to pay, \( \mu_i \alpha + (1 - \mu_i) \beta \), is higher than the listed price \( P \), then buyer \( i \) will buy even when there is no reputation information. Let \( f(\mu^i) \) be the probability that buyer \( i \)'s belief \( \mu^i \) is greater than \( \frac{P - \beta}{\alpha - \beta} \) where \( f(\cdot) \) is an increasing function with \( f(1) = 1 \) and \( f(0) = 0 \). For a seller, the probability of a successful sale when paired with buyer \( i \) is \( \Pr(sale) = \Pr(buy) = \Pr(\mu^i \geq \frac{P - \beta}{\alpha - \beta}) = f(\mu^i) \). Since buyers and sellers are randomly matched in the market, a seller's expected payoff is \( EU_{s,0} = E(f(\mu^i_0) \cdot P) = P \cdot E(f(\mu^i_0)) \) when there is no reputation information. To simplify notations, we denote \( E(f(\mu^i_0)) \) as \( f(\mu_0) \) so \( EU_{s,0} = f(\mu_0)P \).

In the naturally occurring environment, sellers usually can decide what quality of transaction outcomes to provide. We incorporate this factor in the model by assuming sellers can make an effort to influence the quality of transaction outcomes and the game repeats \( T \) periods. If both good and bad sellers put forth effort \( (e = 1) \), they will ship the products with probability 1. If they do not put forth effort \( (e = 0) \), they will not ship the products with probability 1.\(^{13}\) Assume that for good sellers, the cost of making an effort is 0, \( C_{\theta_G}(e = 1) = e(0) = 0 \), and for bad sellers, the cost of making an effort is \( C_{\theta_B}(e = 1) = e(1) > 0 \). To simplify, we assume good sellers will always make an effort, since it costs nothing to them. In this case, a bad seller needs to consider whether to make the effort as part of his strategy. A buyer's propensity to buy at period \( t \) is \( f(\mu^i_{t-1} + (1 - \mu^i_{t-1})\hat{e}_t) \), where \( \hat{e}_t \) is the buyer's expectation of a bad seller's effort. The belief that the seller is a good type in period 2 after seeing a good report in period 1 is:

\[
\mu_1 = \Pr(\theta_G | GR) = \frac{\Pr(GR | \theta_G)\Pr(\theta_G)}{\Pr(GR | \theta_G)\Pr(\theta_G) + \Pr(GR | \theta_B)\Pr(\theta_B)} = \frac{\mu^i_0}{\mu^i_0 + (1 - \mu^i_0)e(1)}.
\]

\(^{13}\) It is possible to assume this probability to be \( \varphi (0 < \varphi < 1) \), and the main result still holds.
Up to period $t$, if all the past reports are good reports, then the updated prior of meeting a good seller is:

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

Once a seller gets a bad report, then buyers know that he must be a bad seller, so the belief that the seller is a good type equals 0, and a buyer’s propensity to buy from him is 0 thereafter. In the last period, $T$, the buyer’s propensity to buy is $\mu_T$, since bad sellers will not make an effort in the last period. Let $\delta$ be the seller’s discount factor to transform the future payoff to the present value. Based on the model setup, we derive the following propositions.

**Proposition 1:** In a complete information market, if $e(1) \leq [1 - (1 - \delta)f(\mu_0)]P$, bad sellers will make a genuine effort for $t = 0$ to $t = T-1$ but will cease to do so in the last period.

Proof: See Appendix A.

In a complete information market where all buyers report, if the cost of effort is less than the benefit of having a good reputation in the future, a bad seller will choose to make an effort and maintain a good reputation for the $T-1$ periods. He will not make an effort in the last period, since the last period’s reputation will not help him gain from future trade.

**Proposition 2:** In an incomplete information market where no one reports, if the rebate cost $0 \leq r < [1 - (1 - \delta)f(\mu_0)]P - e(1)$, then both good and bad sellers will always provide rebates in all periods and in this case, since $e(1) \leq [1 - (1 - \delta)f(\mu_0)]P$, bad sellers will make an effort in the first $T-1$ periods, but not the last period $T$.

Proof: See Appendix B.
No one will report when the reporting cost is more than the maximum internal reporting benefit for all buyers. In this case, bad sellers will have no incentive to make an effort. When the rebate mechanism is introduced, we consider the case that the amount of the rebate is enough to cover some buyers’ reporting costs so that some buyers are willing to report, and we assume that all buyers report honestly if they decide to report. If a bad seller provides the rebate but does not make an effort, he knows that as long as at least one buyer reports negative feedback his type will be revealed. The reason is that good sellers always make an effort to provide good transactions and only bad sellers strategically choose whether to make an effort.

Therefore, if a bad seller decides to provide a rebate, his effort decisions will be the same as in the complete information case as discussed in Proposition 1: if $e(1) \leq [1 - (1 - \delta)f(\mu_0)]P$ is true, a bad seller will make a genuine effort from $t=1$ to $t=T-1$, but will cease to do so in the last period.

We show in appendix B, that there is a pooling equilibrium where sellers will choose to give rebates if the rebate cost $r$ is less than the expected benefit from providing the rebate which is equal to the expected payoff of having a good reputation minus the expected payoff when there is no reputation information in the market at all, i.e., $[1 - (1 - \delta)f(\mu_0)]P - e(1)$. As $e(1) = 0$ for the good sellers and $e(1) > 0$ for the bad sellers, the condition $r < [1 - (1 - \delta)f(\mu_0)]P - e(1)$ is stricter for the bad sellers than for the good sellers. When good sellers provide a rebate, bad sellers may or may not provide a rebate depending on the magnitude of $e(1)$. In the last period $T$, a bad seller has no incentive to make an effort, but he may still offer a rebate because he will not actually incur the cost of the rebate if no one buys from him in the last round.

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14 There may be psychological benefits from reporting, for example, altruism and reciprocation. Feedback can be a way for buyers to reciprocate, especially when the sellers defect. Previous research suggests that people are often willing to incur costs to punish norm violations or reward good deeds (e.g., Andreoni et al., 2003; Ariely et al., 2009; Bénabou and Tirole, 2006; de Quervain et al., 2004; Fehr and Gächter, 2000a; Nikos, 2008; and Xiao and Houser, 2005).
It is worth emphasizing that, as our theory models demonstrate, unlike a “forcing” mechanism suggested in the earlier literature (e.g., Ba et al., 2003 and Dellarocas, 2003b), this precommitment mechanism introduces the idea of an “inducing” mechanism which has the following features: (1) it provides a precommitment option for sellers to signal quality rather than requiring them to do so; (2) it allows both good sellers and bad sellers to coexist in the market, but makes it possible for buyers to distinguish between them; thus, (3) it can induce bad sellers to cooperate over time.

We next describe our experiments to examine empirically how people behave when this precommitment option is provided.

III. Experimental Design

Our experiment is based on a buyer-seller trust game modified from Bolton et al. (2004). We design four treatments to examine how the feedback reporting cost influences trading behavior and, most importantly, whether the rebate option serves as a signaling device and improves market efficiency. The four treatments are: (1) computer automatic feedback treatment ($Auto_fb$); (2) a higher feedback cost treatment with cost = 10 ($C10$); (3) a lower feedback cost treatment with cost = 5 ($C5$); and (4) the higher feedback cost treatment with a rebate = 5 ($C10r5$). Each treatment consists of ten rounds. In each round, each subject is randomly paired with another subject. One round is randomly selected as the payment round. Each round consists of two stages. The first stage is exactly the same in each treatment. Treatments differ in the second stage.

The first stage is a buyer-seller game (Bolton and Ockenfels, forthcoming) described in Figure 1. In this stage, subjects are paired anonymously, with one acting as a seller and the other acting as a buyer. If the buyer decides not to buy the product, the game will end and each participant earns 35E$ (experiment dollars). If the buyer decides to buy the product, then the seller decides whether to ship the product. If the
seller ships the product, each participant earns 50E$. If the seller does not ship the product, the seller earns 60E$ and the buyer earns 10E$.

The first stage is followed by a second stage where the seller receives feedback. The seller is informed of the feedback he receives in each round. Starting from the second round, each buyer sees the paired seller’s feedback from all the previous rounds.

**Computer automatic feedback treatments (Auto_fB)**

In this treatment, the computer automatically records the feedback for each seller. If the buyer did not buy the product in the first stage, then the seller has no decision to make. In this case, the seller receives “N/A (no report).” If the buyer bought the product and the seller shipped the product, the computer automatically leaves a “+ (positive)” feedback for the seller. If the seller did not ship the product, the seller receives a “- (negative)” feedback. All these are common knowledge. Therefore, in this treatment, the reputation mechanism is complete and perfect in that the costless feedback truthfully and fully reveals the seller’s behavior in the past (sees Bolton and Ockenfels, forthcoming).

**Feedback cost 10 treatment (C10) and feedback cost 5 treatment (C5).** In both the C10 and C5 treatments (see Figure 2 and 3), after the buyer purchases the product and the seller makes the shipping decision, the buyer can leave feedback for the seller at the cost of 10E$ in the C10 treatment or 5E$ in the C5 treatment.

As we mentioned earlier, if there is some psychological benefit to reporting, buyers might be willing to incur some monetary cost to report. Ex ante, we do not know the magnitude of this nonmonetary value of reporting. We speculate that, for some buyers, the psychological benefit of reporting may be higher than the monetary cost of 5E$ and these buyers will report in this treatment. Our goal is to test the effectiveness of the rebate mechanism when the feedback system is ineffective due to

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15 The corresponding payoffs in the model setup are \( V_b = 40, V_s = 10 \), and \( P = 25 \).
the cost of reporting. We design the C10 treatment where the reporting cost is 10E$.
This is the highest reporting cost we could impose so that the buyer would not have a
negative earning from the game (since when the buyer is cheated, her payoff is 10E$).
When we derive the hypotheses below, we assume the reporting cost of 10E$ is high
enough that the buyer will not report in this treatment.

If a buyer decides to pay the price to rate her seller, the buyer can leave
positive, negative, or neutral feedback. If the buyer decides not to rate the seller, the
seller will receive “N/A (no report)” as feedback for that round. In addition, if the
buyer does not purchase the product, the paired seller also receives feedback of “N/A
(no report)” in that round. That is, if the seller has feedback of “N/A (no report),” this
means that either the buyer did not purchase the product or the buyer purchased but
did not report feedback. We design the feedback mechanism this way to closely
mimic real online markets where there is no feedback, both when there is no trade and
when the buyer is not willing to leave feedback.

**Feedback cost 10 with rebate 5 treatment (C10r5)**

We introduce a rebate mechanism in the C10 treatment (see Figure 4) where we
assume the high cost of reporting leads to an ineffective reputation mechanism. The
design of the C10r5 treatment is the same as the C10 treatment except that at the
beginning of each round, before the buyer decides whether to purchase the product,
the seller first decides whether to provide a rebate of 5E$ to cover half of the
reporting cost the buyer will incur if she leaves feedback for the seller. If the seller
provides the rebate and the buyer pays 10E$ to report the feedback in the second stage,
there is a 5E$ transfer from the seller to the buyer at the end of the round. On the
other hand, as long as the buyer does not leave feedback, the 5E$ rebate transfer does
not happen even if the seller provides the rebate. Each buyer can see whether her
seller provides the rebate when deciding whether to purchase the product.

We design the rebate value equal to 5E$ so that our treatments allow us to
examine the signaling role of rebate. In the C10r5 treatment, if the seller provides a
rebate of 5E$, the buyer’s payoff scenario is equivalent to that of the C5 treatment. Similarly, if the seller does not provide a rebate of 10E$, the buyer’s payoff scenario is equivalent to that of the C10 treatment. Thus, by comparing buyers’ decisions in the C5 (or C10) treatment and in their payoff equivalent scenario in the C10r5 treatment, we can draw inferences regarding the nonmonetary value of sellers’ rebate choices to buyers.16

Note that the feedback each seller receives is either positive, negative, neutral, or N/A. Since sellers in each treatment have two decisions to make—rebate and ship—then in principle, buyers can leave feedback based on their satisfaction regarding not only the seller’s shipping decision but also the rebate decision. For example, buyers might leave negative feedback when the seller did not provide the rebate even if the seller shipped the product. As we report in Section V.A., in this treatment we do not observe any incidence of feedback decisions that are inconsistent with the seller’s shipping decision (i.e., positive feedback for “not ship” and negative feedback for “ship”).

III. B Procedure
The experiment was conducted at the Pittsburgh Experimental Economics Laboratory using z-tree (see, Fischbacher, 2007). Subjects were randomly and anonymously assigned a role and the role was fixed in all ten rounds. Each subject was randomly and anonymously rematched with another subject in each round. One round was randomly chosen as the payoff round. We ran 13 sessions in total: three sessions for each of the Auto_fb, C5, and C10 treatments and four sessions for the C10r5 treatment. Each session lasted less than one hour. No one could participate in more than one session. Each subject was paid $5 for showing up in addition to the earnings from the games. The exchange rate was 5E$ = $1. Subjects were paid privately. We

16 Note that if we design a rebate value equal to 10E$, when the seller provides a rebate, the buyer’s net reporting cost will be zero. To provide a cost equivalent treatment for this condition, we will need another treatment where buyers can decide whether to leave feedback at no monetary cost (which differs from the Auto_fb treatment).
obtained observations on 214 subjects: 24 pairs in Auto_fb; 23 pairs in C5; 24 pairs in
C10; and 36 pairs in C10r5.

IV. Hypotheses
In this section, we derive predictions of sellers’ and buyers’ decisions based on our
theory framework discussed in Section II.

Buyers’ reporting decisions
Hypothesis 1: Reporting cost has a negative effect on buyers’ reporting behavior:
Pr (report): 0 \approx C10 < C5 <1.

We assume that buyers are risk neutral and utility maximizers. As we
mentioned earlier, we also consider that there might be some psychological benefit of
reporting feedback. We assume that for some buyers, their psychological benefit of
reporting may be higher than the monetary cost of 5E$ and for others, the
psychological benefit of reporting is lower than 5E$. Thus, some but not all buyers
will report in this treatment (Pr (report): 0 <C5 <1). We also assume the reporting
cost of 10E$ is high enough to overwhelm the psychological benefit of reporting and
thus we predict Pr(report): 0 \approx C10.

Buyers’ purchasing decisions
Hypothesis 2: Buyers are less likely to buy when reporting is costly:
Pr(buy): C10 <C5 \approx Auto_fb.

As we mentioned earlier, a good seller always makes an effort, so he will
always get positive feedback, if any. A bad seller may choose to make an effort. If he
does not make an effort in some rounds and the buyers in those rounds report, then he
will definitely receive some negative feedback. As a consequence, no buyer will buy
from him in the future. The reason is that good sellers always make an effort to
provide good transactions and only bad sellers strategically choose whether to make
an effort. Thus, as long as at least one buyer reports negative feedback, a bad seller who cares about future payoff will choose to make an effort.

In the C10 treatment, we assume that the reporting cost is so high that no one reports feedback. Consequently, bad sellers will not make an effort, and only optimistic buyers will buy. In the C5 treatment, bad sellers know that if they fail to make an effort, some buyers may leave feedback. Consequently, they will make an effort for higher future payoffs. Thus, the probability of purchasing in the C5 treatment is about the same as that in Auto_fb case where all reports are revealed, and both of these have a greater probability than the C10 treatment.\(^\text{17}\)

**Hypothesis 3:** Buyers take “no rebate” as a signal of a bad seller:

\[
Pr^{C10}(\text{buy}) > Pr^{C10r5}(\text{buy} | \text{No Rebate})
\]

\[
Pr^{C10r5}(\text{buy} | \text{Rebate}) > Pr^{C10r5}(\text{buy} | \text{No Rebate}).
\]

In the theoretical model, both types of sellers will choose to give rebates as long as it is profitable for bad sellers to mimic good ones. Therefore, providing “rebate” does not provide any information about the type of seller, but providing “no rebate” does. The reporting cost in the C10 treatment is the same as in the C10r5 treatment when the seller does not offer a rebate, but the latter case provides additional information about the seller’s quality. Thus, ceteris paribus, buyers should be less likely to buy the product in the latter case than in the former.

Comparing the case in the C10r5 treatment where the seller offers a rebate with the case where the seller does not offer a rebate, buyers expect the seller to be more likely to cooperate in the former than in the latter case. Additionally, the reporting cost for the buyer is lower in the former case than in the latter case. Thus,

\(^{17}\) If our assumption that no one reports in C10 is invalid (i.e., some buyers still report or sellers believe that some buyers will report), in the pure adverse selection model the result in the C10 treatment would be indifferent from that in the C5 treatment. In the mixed model case, bad sellers would make an effort to ship the products like in the C5 and Auto_fb treatments. As a result, the probability of buying in the C10 treatment would be indifferent from the C5 and Auto_fb treatments.
we predict that in the C10r5 treatment, buyers will be more likely to buy when the seller offers a rebate than when the seller does not.

**Sellers’ rebate and shipping decisions**

**Hypothesis 4**: Sellers are less likely to ship when reporting is costly:

\[
\Pr(\text{ship}): \quad C10 < C5 \quad \approx \quad \text{Auto}_{-}\text{fb}.
\]

In the mixed model, the analysis of sellers’ shipping decisions is similar to the analysis in Hypothesis 3 because buyers’ buying decisions depend on how they think sellers will behave. In the C10 treatment, we assume that no one will report. Thus, bad sellers will not put forth an effort, and only optimistic buyers will buy. In the C5 treatment, at least some buyers will report. Thus, as in the Auto_fb treatment, bad sellers in C5 treatment will make an effort in order to have future payoffs. As a result, the probability of shipping is higher than in the C10 treatment.\(^{18}\)

**Hypothesis 5**: Sellers’ decisions not to offer a rebate signals an intention to defect:

\[
\Pr^{C10r5}(\text{ship} | \text{Rebate}) < \Pr^{C10r5}(\text{ship} | \text{No Rebate}).
\]

Our theoretical framework discussed earlier suggests that bad sellers will mimic good sellers by choosing the rebate option if it is profitable for them to continue providing rebates. Although the decision to provide rebates does not help us identify good sellers and bad sellers, a decision not to provide a rebate signals the seller’s intention to defect. Therefore, we predict that in the C10r5 treatment, sellers who do not provide a rebate will be less likely to ship the product than those who offer a rebate.

From our hypotheses, we expect that under the rebate mechanism, market efficiency is increasing with the frequency of rebates offered by the sellers. We define efficient trades as cases where the buyer buys and the seller ships. As discussed in

\(^{18}\) If our assumption that no one reports in the C10 treatment is invalid (i.e., some buyers still report or sellers believe that some buyers will report), then bad sellers would make an effort to ship the products like in the C5 and Auto_fb treatments. As a result, the probability of shipping in the C10 treatment would be indifferent from the C5 and Auto_fb treatments.
Hypothesis 3, when the rebate mechanism is introduced, a buyer is more likely to buy when the seller offers a rebate than when the seller does not offer a rebate. Meanwhile, Hypothesis 5 suggests that, under the rebate mechanism, the shipping rate is higher when sellers offer a rebate than when sellers do not offer a rebate. Combining these two hypotheses, we predict that the more often a buyer receives rebates, the more efficient trades the buyer can achieve.

V. Results
In this section, we first report results of buyers’ decisions, followed by results of sellers’ decisions. We then examine how the rebate mechanism affects market efficiency.

V. A. Buyers’ feedback reporting decisions
Our data suggest that buyers report feedback honestly most of the time in the C5, C10, and C10r5 treatments. Among the 1070 transactions in all treatments, only three buyers left negative or neutral feedback to a seller who shipped the product. In all the other cases where the buyer chose to leave feedback, she left positive feedback for cooperative sellers and negative feedback for noncooperative sellers. Thus, in the following analysis, we focus only on the frequency of reporting and not the honesty of reporting.

We first compare buyers’ feedback reporting behavior in the C5 and C10 treatments to test Hypothesis 1.

**Result 1.** The cost of feedback has a significant negative effect on the buyer’s reporting decision.

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19 One buyer in the C5 treatment left negative feedback in one round after the seller shipped the product. The feedback behavior of this buyer in the following rounds, however, is consistent with the shipping decisions of her paired seller. So it might be just a mistake made by this buyer in the early rounds of the session. One buyer in the C10 treatment left neutral feedback in one round after the seller shipped the product. Also, one buyer in the C10r5 treatment left neutral feedback after her seller provided a rebate and shipped the product.
We calculate the feedback reporting rate among those buyers who purchased the product (see Table 1) in each treatment. Supporting our Hypothesis 1, the cost of feedback has a significant and negative effect on the buyer’s reporting decision. About 32% of buyers left feedback for the seller when the cost of doing so was 5E$. In contrast, when the reporting cost was 10E$, only about 10% of buyers left feedback. Using the data from Treatment C10 and Treatment C5, we ran a random individual effect logit regression analysis of the probability of buyers who bought the product to leave feedback (see Table 2 column (1)). The independent variables include round, dummy for the final round, and two treatment dummies. The coefficients of the two treatment dummies are significantly different (chi-square test, p=0.01).

Previous research has shown that people are more willing to punish bad behavior than to reward good behavior (e.g. Keysar, et al. 2008). If reporting feedback is a way for the buyer to reciprocate to the seller, we should expect that buyers would be more willing to leave negative feedback when the seller did not ship the product than to leave positive feedback when the seller shipped the product. In light of this, we next investigate how buyers left feedback in the C5 and C10 treatments and compare how cost affects a buyer’s propensity to leave feedback when the seller ships versus when the seller does not ship the product.

Result 2. Buyers are more likely to leave feedback when the seller does not ship the product than when the seller ships the product. Moreover, the propensity of buyers to leave feedback is more sensitive to the reporting cost when the seller is cooperative than when the seller defects.

As shown in Table 1, in both the C5 and C10 treatments, buyers were more likely to leave feedback when the seller did not ship the product than when the seller

---

20 In all the regression models reported below, we always first consider the possible session effects by including dummies for each session in the regressions. We find the session dummies are not jointly significant in any regression (chi-square test, p>0.10). Thus, we report regressions without including session dummies.

21 All the coefficient comparison tests reported henceforth are chi-square tests with two-tail p-values.
shipped the product (50% vs. 28% in the C5 treatment and 40% vs. 4% in the C10 treatment, respectively). Thus, reporting behavior is negatively biased.

To provide statistical evidence, we ran a random individual effect logit regression analysis of feedback reporting behavior (see Table 2 column (2)) similar to the regression analysis reported in Table 2 column (1). The only difference is that we separated the cases of cooperative sellers from the noncooperative sellers. Thus, the independent variables include round, last round dummy, interactions of treatment dummies, and whether the seller shipped the product. We find that the coefficient of C10ship is significantly different from that of C10noship and the coefficient of C5ship is significantly different from that of C5noship (p<0.01).

Moreover, the coefficient of C10noship is not significantly different from C5noship (p=0.19). However, the coefficient of C10ship is significantly different from C5ship (p<0.01). These results suggest that the propensity of buyers to leave feedback is less sensitive to the reporting cost when the seller defects than when the seller cooperates. Thus, higher reporting costs lead to more negative-biased reporting behavior.22

Next, we consider the effect of rebates on buyers’ reporting behavior.

**Result 3.** *When the seller cooperates, a buyer is more likely to leave feedback when the seller offers a rebate than when the seller does not offer a rebate.*

Table 1 also reports the feedback reporting rate in each scenario in the C10r5 treatment depending on whether the seller offered a rebate and whether the seller shipped the product. It shows that, when the seller shipped the product, the buyer is

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22 One explanation is that, as sellers' decision is binary (ship vs. not ship), buyers who are willing to incur the cost to leave the feedback may implicitly collude and take N/A (no feedback) as an indicator that the seller shipped the product and negative feedback as indicating the seller did not ship. Thus, these buyers can economize on the cost of building a reputation system by just leaving negative feedback when the sellers did not ship and not leaving positive feedback when the sellers shipped. In C10 treatment, the increased cost of reporting may facilitate this collusion and buyers are thus much less likely to leave positive feedback.
more likely to report when the seller offered a rebate than when the seller did not offer a rebate (26% vs. 12%). In contrast, when the seller did not ship the product, the reporting rate is lower when the seller provided a rebate than when the seller did not provide a rebate (39% vs. 62%) although as we will show this difference is not statistically significant.

To provide statistical evidence of the effect of a rebate on buyers’ reporting decisions, we expand the random effect logit regression model in Result 2 by including the data from the C10r5 treatment. For C10r5 treatment data, we also separate the cases where the seller cooperated from the cases where the seller defected and the cases where the seller provided a rebate from the cases where the seller did not provide a rebate. The results of the regression are reported in Table 2 column (3). First, we find that the coefficient of C10r5_rebship is significantly different from C10r5_norebship (p<0.01) and C10ship (p<0.01), but not significantly different from C5ship (chi-square test, p= 0.96). Meanwhile, the coefficient of C10r5_norebship is significantly different from C5ship (p=0.02), but not significantly different from C10ship (p=0.56). These results suggest that rebates, by compensating for the cost, can make buyers more likely to leave feedback when sellers ship the product.

On the other hand, all the coefficients of the independent variables related to the cases where the sellers failed to ship are not significantly different between each other. For example, the coefficient of C10r5_rebnoship is not significantly different from that of C5noship or C10noship or C10r5_norebnoship (p>0.10). The coefficient of C10r5_norebnoship is not significantly different from that of C5noship or C10noship (p>0.10). These results suggest that rebates have no significant effect on buyers’ reporting decisions when sellers fail to ship the product.

Thus, our data suggest that if buyers’ reporting behavior is negatively biased, as shown earlier, then offering a rebate can reduce such negative bias by increasing the reporting rate when sellers cooperate. It is also worthwhile to note that, as we mentioned earlier, buyers report feedback honestly most of the time regardless of
whether a rebate is provided. In other words, our data suggest that a seller’s rebate decision affects the propensity to report, but not the honesty of the feedback.

V. B. Buyers’ purchasing decisions

To test Hypotheses 2 and 3, we first report the comparison of buyers’ purchasing behavior in the Auto_fb, C5, and C10 treatments to see how buyers’ purchasing behavior is affected by the feedback reporting cost. We then compare buyers’ purchasing behavior in the C10r5 treatment with Auto_fb, C5, and C10 to explore how it is affected by the rebate mechanism.

As shown in Table 1, on average, buyers purchase the product 79% of the time in the Auto_fb treatment, 70% in the C5 treatment, and 68% in the C10 treatment. This result is consistent with our Hypothesis 2. However, these differences are not statistically significant. We start our analysis with a simple random individual effect logit regression model of buyers’ purchasing decisions, including only round, last round dummy, and three treatment dummies as independent variables. The results are reported in Table 3 column (1). We find that the coefficients of C5, C10, and Auto_fb are not jointly significantly different from each other (p=0.23). Nor is any pairwise comparison of the coefficients of any two treatments significant (p>0.10).

**Result 4.** Supporting Hypothesis 3, buyers are significantly less likely to buy the product when the seller did not provide the rebate in the C10r5 treatment than when the seller provided the rebate or when there is no rebate opportunity at all.

As reported in Table 1, in the C10r5 treatment, buyers purchase the product about 84% of the time if the seller provides a rebate (the highest purchase rate among all the conditions), but only about 36% of the time if the seller does not provide the rebate (the lowest purchase rate among all the conditions). To provide statistical evidence comparing the purchase rates in each condition, we further expand our regression model discussed above (Table 3 column (1) regression) by including data from all four treatments.
First, we add dummies of whether the seller provided a rebate to the buyer in this round ($C10r5\_noreb_{i,t}$ and $C10r5\_reb_{i,t}$). We also expand our regression model by adding the current matched seller’s reputation variables and the shipping decision of the matched seller in the previous round. Previous research shows that the reputation history of sellers has a different effect on buyers’ decisions depending on when the feedback is reported. In particular, the most recent feedback is more important for the buyer than earlier feedback (see Bolton et al., 2005). In light of this, we separate the most recent feedback in the previous round from the other feedback received in the past (round 2 to round $t-2$). For each buyer $i$ in round $t$, we calculate the total amount of positive feedback and negative feedback received by the matched seller from round 2 to round $t-2$, respectively.

Thus, the independent variables in the regression include: round ($t$), final round dummy, C5 treatment dummy (C5), C10 treatment dummy (C10), Automatic feedback treatment dummy (Auto_fb), total number of positive feedback the matched seller received up to round $t-2$ ($\sum_{t=1}^{t-2} \text{Positive } fb_{i,t}$), total number of negative feedback the seller received up to round $t-2$ ($\sum_{t=1}^{t-2} \text{Negative } fb_{i,t}$), whether the seller received positive feedback in the previous round ($\text{Positive } fb_{i,t-1}$), whether the seller received negative feedback in the previous round ($\text{Negative } fb_{i,t-1}$), whether the seller shipped the product in the previous round ($\text{Ship}_{i,t-1}$), and whether the seller provided a rebate to the buyer in this round ($C10r5\_noreb_{i,t}$ and $C10r5\_reb_{i,t}$). The results are reported in Table 3 column (2).

Consistent with previous literature (see the survey paper Dellarocas 2003a), the regression results show that buyers are more likely to buy if the seller received positive feedback in the previous round and less likely to buy if the seller received negative feedback in the previous round (the coefficient of $\text{Positive } fb_{i,t-1}$ is significantly positive and the coefficient of $\text{Negative } fb_{i,t-1}$ is significantly negative). Buyers also take into account the total amount of negative feedback received by the seller in the past when deciding whether to buy. The more negative
feedback the seller received two rounds ago, the less likely the buyer will be to buy the product (the coefficient of $\sum_{t=1}^{T-2} Negative fb_{i,t}$ is significantly negative).

Interestingly, however, the amount of positive feedback received two rounds ago does not have a significant effect on a buyer’s purchasing decision (the coefficient of $\sum_{t=1}^{T-2} Positive fb_{i,t}$ is positive but not significant).

The regression results support Hypothesis 3: “not providing rebate” provides information about the types of sellers, but “providing rebate” does not. To see this, first note that buyers are more likely to buy when the seller offers the rebate than when the seller does not (the coefficient of $C10r5\_noreb_{i,t}$ is significantly lower than that of $C10r5\_reb_{i,t}$, $p<0.01$). Second, when the seller does not provide the rebate, the buyer is much less likely to buy than when the seller does not have the rebate opportunity at all (the coefficient of $C10r5\_noreb_{i,t}$ is significantly lower than that of $C10$, $p<0.01$). On the other hand, providing the rebate does not make buyers more likely to buy than when the rebate mechanism is not available (the coefficient of $C10r5\_reb_{i,t}$ is not significantly different from that of $C5$, $p=0.75$).

We next provide evidence that the seller’s rebate decision is indeed a credible signal of his cooperativeness.

V. C. Sellers’ rebate and shipping decisions

We first test Hypothesis 4 by investigating how sellers’ shipping decisions may differ between treatments due to the reporting cost. Then, to test Hypothesis 5, we investigate how sellers make rebate decisions and how rebate decisions are correlated with shipping decisions.

We report sellers’ shipping rates in Table 1. Consistent with Hypothesis 4, the shipping rate is highest among the three non-rebate treatments in the Auto_fb treatment (88%) and lowest in the C10 treatment (81%). The difference, however, is small.

Similar to the analysis of buyers’ decisions, to provide statistical evidence, we first conduct a random individual effect logit regression analysis of the sellers’
shipping decisions by including only round variables, C10, C5, and Auto_fb treatment dummy variables. This allows us to see whether the sellers’ shipping decisions overall are significantly affected by the feedback reporting cost. The regression results are reported in Table 4. We find that the coefficients of the three treatment dummies are not jointly significantly different from one another (p=0.76). Nor is any pairwise comparison of the coefficients of any two treatments significant (p>0.10). Thus, although our data suggest that the shipping rate is decreasing in the reporting cost, this effect of the reporting cost is not significant.

We next examine how sellers make rebate decisions and how the rebate decision is correlated with sellers’ shipping decisions.

**Result 5.** Sellers are more likely to offer the rebate if they did not offer the rebate in the previous round and the buyer did not buy the product than if they did not offer the rebate in the previous round and the buyer bought the product.

In the C10r5 treatment, every seller provided a rebate at least once to the buyer. On average, sellers chose to offer a rebate 75% of the time. About 90% of sellers chose to offer a rebate at least half of the time. The distribution of rebate frequency is plotted in Figure 5.

We have shown above that most buyers in the C10r5 treatment did not purchase if the seller did not offer the rebate. Sellers who did not offer the rebate may learn from their experience that they are less likely to sell their product if they do not provide a rebate and thus learn to offer rebates over time. To examine whether sellers’ rebate decisions are indeed affected by buyers’ decisions, we calculate sellers’ frequency of offering the rebate in each of four cases, depending on whether the seller provided the rebate in the previous round $t-1$ and whether the buyer bought the product in that round: (1) seller provided the rebate and buyer bought the product in round $t-1$; (2) seller provided the rebate but buyer did not buy the product in round $t-1$; (3) seller did not provide the rebate but buyer bought the product in round $t-1$; and (4) seller did not provide the rebate and buyer did not buy the product in round $t-1$. We
find that if the seller provided a rebate in the previous round, her decision on rebate in the current round is not greatly affected by whether the buyer bought the product or not in the previous round (90% vs. 97%). In contrast, if the seller did not provide a rebate in the previous round, he is much more likely to provide the rebate in the current round if the buyer did not purchase the product than if the buyer purchased the product in the previous round (51% vs. 20%).

To provide statistical evidence on these differences, we ran a random individual logit regression analysis of sellers’ rebate decisions in round $t$. The independent variables include only the four dummies corresponding to each of the four scenarios mentioned above. We find that the coefficients for the first two scenarios when the seller provided the rebate in round $t-1$ (buyer bought the product in round $t-1$ vs. did not buy the product) are not significantly different ($p=0.15$), but those for the second two scenarios where the seller did not provide the rebate in round $t-1$ (buyer bought the product in round $t-1$ vs. did not buy the product) are significantly different ($p=0.01$).

Furthermore, we see more and more sellers offering the rebate over time. Figure 6 plots the proportion of sellers who offer the rebate from round 1 to round 10. The slope is significantly positive ($p=0.01$), suggesting that over time sellers learn that providing the rebate can increase their chances of making a profit.

**Result 6.** The more often a seller provides rebates, the more likely the seller will ship the product.

To examine whether sellers’ shipping decisions are correlated with their rebate decisions, we calculate for each seller, his frequency of offering rebates and the frequency of shipping the product when the buyer chooses to buy the product. We find that when sellers provide a rebate no more than half of the time, their shipping rate is about 63%; in contrast, this rate is 82% for sellers who offer a rebate more than half of the time. To test whether the correlation between rebate and shipping decisions is significant, we ran a Tobit regression analysis of seller $i$’s average shipping rates in
the C10r5 treatment using the frequency of rebates seller \( i \) offered to the matched buyers as the independent variable. We find that the coefficient of this independent variable is significantly positive (p<0.01).

V. D. Market efficiency

To test the prediction that under the rebate mechanism the market efficiency is increasing with the frequency of rebates offered by the sellers, we first examine the number of efficient trades (i.e., the case where the buyer bought and the seller shipped the product) in each treatment. We then compare the earnings of buyers and sellers for each treatment.

**Result 7. The feedback reporting cost reduces the proportion of efficient trades.**

*Under the rebate mechanism, the number of efficient trades is increasing in the frequency of rebate provided to the buyer.*

We define efficient trades as the cases when the buyer bought and the seller shipped the product. Figure 7 plots the proportion of efficient trades in each treatment. In the C10r5 treatment, we also separate the case where sellers provide the rebate from the case where they do not. Figure 7 shows that the proportion of efficient trades is decreasing in the feedback reporting cost. The number of efficient trades is highest in the case where the seller offers the rebate in the C10r5 treatment and lowest when the seller fails to offer the rebate in the C10r5 treatment. To provide statistical analysis of efficient trades, we define a variable \( Ef\text{trade}_{i,t} \) = 1 if the buyer bought and received the product, and \( Ef\text{trade}_{i,t} = 0 \) if the buyer did not buy or bought but the seller failed to ship the product. We then calculate the average number of efficient trades over ten rounds for each buyer:

\[
Avg\_Ef\text{trade}_t = \frac{\sum_{t=1}^{10} Ef\text{trade}_{i,t}}{10}.
\]

To examine the effect of rebates on market efficiency, for each buyer in the C10r5 treatment, we calculated over the ten rounds the average proportion of times
she was offered a rebate from a matched seller before deciding whether to purchase
the product:

\[
\text{Avg}_{\text{reb}}_{\text{tms}} = \begin{cases} 
\sum_{t=1}^{10} \text{C10r5}_{\text{reb}}_{i,t}, & \text{if C10r5 treatment} \\
0, & \text{if Auto}_{\text{fb}}, \text{C5, or C10 treatment}
\end{cases}
\]

where \( \text{C10r5}_{\text{reb}}_{i,t} = 1 \) if buyer \( i \) was offered a rebate in round \( t \) in the C10r5 treatment. We then ran an OLS regression analysis of \( \text{Avg}_{\text{Eftrade}}_{i} \). The independent variables include four treatment dummy variables and \( \text{Avg}_{\text{reb}}_{\text{tms}}_{i} \). The regression results are reported in Table 5. We find that the coefficient of C10 is significantly different from Auto_{\text{fb}} (p=0.04), although C5 is not significantly different from Auto_{\text{fb}} (p=0.12). This suggests that a high reporting cost can reduce the number of efficient trades in the market. The regression result also reveals that the coefficient of C10r5 is significantly different from those of Auto_{\text{fb}} (p=0.01) and C5 (p=0.05), but not significantly different from C10 (p=0.07). This indicates that under the rebate mechanism, if no rebate is ever offered the number of efficient trades is just the same as when there is no rebate mechanism.

On the other hand, the coefficient of \( \text{Avg}_{\text{reb}}_{\text{tms}}_{i} \) is significantly positive, which suggests that the more often a buyer receives a rebate from the seller, the more efficient trades the buyer achieves. The magnitude of the coefficient of \( \text{Avg}_{\text{reb}}_{\text{tms}}_{i} \) also suggests that if a buyer always receives a rebate from the matched seller (i.e., \( \text{Avg}_{\text{reb}}_{\text{tms}}_{i}=1 \)), then the number of efficient trades can be as many as in the Auto_{\text{fb}} treatment.

**Result 8.** When the rebate mechanism is available, buyers’ and sellers’ earnings are increasing in the number of rebates offered by sellers.

Similar to the analysis of the effect of rebates on efficient trades, we examine the effect of rebates on the buyer’s and the seller’s earnings using the same method. We calculate the average earnings over ten rounds for each buyer and seller. We then run an OLS regression analysis of buyers’ earnings using the same independent variables as in the regression in Table 5. The results are shown in Table 6. We find
the coefficients of C10 and C5 are significantly lower than that of Auto_fb (p<0.01 in both cases), but not different from one another (p=0.75). This suggests that buyers earn significantly less when reporting feedback is costly than when the reputation can be automatically recorded at no cost to the buyers.

The coefficient of C10r5 is significantly lower than the coefficients of the three other treatments (p<0.01 for all the pair-wise tests). This indicates that if buyers are never offered a rebate, they will earn less than if there is no rebate mechanism (i.e., C10 treatment). On the other hand, the coefficient of Avg_rebtms_i is significantly positive, suggesting that a buyer who receives rebates more often can also earn more. Indeed, the regression results suggest that if a buyer receives rebates every time (i.e., Avg_rebtms_i=1), she can earn almost as much as the buyers in the Auto_fb treatment. If a buyer receives rebates more than 80% of the time (i.e., Avg_rebtms_i=0.8), she can earn more than the buyers in the C5 or C10 treatments. Again, this suggests that the rebate not only compensates a buyer’s cost but also enables buyers to make efficient trades.

Using the same regression analysis, we next discuss the effect of the reporting cost and the rebate mechanism on sellers’ earnings. The regression results are reported in Table 6. We find that the reporting cost does not significantly affect sellers’ earnings. In particular, the coefficient of neither C5 nor C10 is significantly different from Auto_fb (p=0.13 and 0.08, respectively). However, the coefficient of C10r5 is significantly different from C10, C5, and Auto_fb (p=0.056, 0.04, and 0.00, respectively). This suggests that when the rebate mechanism is available, not providing the rebate makes the seller earn even less than if the rebate mechanism is not introduced.

On the other hand, the regression results also suggest that providing a rebate positively affects sellers’ earnings (coefficient of Avg_rebtms_i is significantly positive). The positive coefficient of Avg_rebtms_i indicates that if the seller offers rebates 80% of the time, he can earn more than she does in the corresponding no-rebate environment (i.e., the C10 treatment). To earn as much as the sellers in the
C5 treatment, the seller needs to provide rebates about 90% of the time. If the seller provides a rebate every time, his earnings will be just slightly lower than in the Auto_fb treatment.

VI. Discussion
Reputation information is crucial to build cooperation in markets where information is asymmetric. However, reputation systems that rely on voluntary feedback have the problem of missing or biased reports, and thus their effectiveness in promoting trust and trustworthiness in the markets is limited. In this paper, we propose and examine an innovative precommitment mechanism (rebate for feedback) aimed at inducing participation in reputation systems and promoting voluntary cooperation in markets where information is asymmetric. We show, both theoretically and experimentally, that the advantage of this precommitment mechanism is to improve the reputation system and market efficiency without requiring buyers or markets to bear the reporting cost.

Our experimental data support our hypothesis about the effectiveness of the rebate mechanism. In particular, the monetary rebate offer from the seller provides buyers a credible signal as to the seller’s quality. Sellers who offer more rebates are more likely to cooperate. The rebate mechanism can improve market efficiency in that the more often rebates are offered, the more efficient trades occur. The market designer may thus consider incorporating a precommitment device, such as the rebate mechanism studied here, into the real market when there is an asymmetric information problem.

In our study, we use a simple unilateral feedback system where only buyers can leave feedback to sellers. We find that a buyer’s propensity to report is more sensitive to the reporting cost when a seller cooperates than when a seller defects. Consistent with this result, a rebate offer increases a buyer’s propensity to leave feedback when the seller cooperates, but has no significant effect when the seller defects. Thus, the feedback we observe from our experiment is negatively biased (see
also Gazzale and Khopkar, 2008). This is in contrast to the empirical observations from eBay’s website, where 99% of feedback was positive in the eBay-like bilateral feedback system (see Resnick and Zeckhauser, 2002, Cabral and Hortacsu, 2010, and Bolton et al., 2009).\(^{23}\)

One explanation is that a bilateral feedback system, in contrast to the unilateral feedback reporting system studied in this paper, creates asymmetric costs for reporting (the cost for reporting negative feedback is higher than that for reporting positive feedback). One of the reasons for these asymmetric costs is the fear of retaliation. When the feedback system is bilateral, a strategic seller has the opportunity to leave negative feedback for a buyer who leaves him negative feedback.\(^{24}\)

Another possible explanation is that negative feedback reporting, as a way to punish the counterparty, is determined by whether the reporter thinks the counterparty has a negative intention. In our experiment, the lower payoff is caused only by the seller’s dishonesty. Thus, it is always clear to buyers whether the seller intentionally cheated. However, in the naturally occurring online trading market, the final trading outcomes always bear some degree of uncertainty. For example, the seller might have shipped the product on time but the package was delayed by the post office. Previous studies suggest that punishment occurs much more frequently when the negative outcomes are determined intentionally by a person than when decided randomly (Blount, 1995; Fehr and Gächter, 2000b; and Houser and Xiao, 2010). It follows that buyers might tend not to leave negative feedback if they are uncertain about whether a seller harmed them intentionally.

The precommitment mechanism introduces the idea of how to design institutions that allow exchange parties to solve the asymmetric information problem among themselves and reach a win-win outcome. The monetary rebate mechanism

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\(^{23}\) These data were collected prior to eBay’s policy to ban sellers from leaving negative feedback to buyers in May 2008.

\(^{24}\) Li (2010b) and Dellarocas and Wood (2008) suggest that fear of retaliation is a concern buyers have about leaving negative feedback.
examined in this study provides one example of how to design a precommitment mechanism. Our study provides direction for further research on how to design different types of precommitment devices based on the causes of asymmetric information problems. For example, in the naturally occurring online market, buyers may not be willing to leave negative feedback because sellers can retaliate by leaving negative feedback for the buyer. In this case, the market maker could design a precommitment device to allow sellers to choose an “automatic feedback for the buyer” option. If a seller chooses this option, the market maker will leave feedback on behalf of the seller contingent on receiving payments, and thus the seller precommits to the buyer that he will not retaliate against her.

In this paper, we take a first step to test the effectiveness of a precommitment mechanism as a type of inducing mechanism to promote exchange efficiency in a listed-price market. Although we focus on the effect of rebate on the probability of purchasing, it is worth noting that the precommitment mechanism can affect the exchange outcomes in other domains. For example, in an auction market, providing rebates may benefit sellers by raising the price of the products. We are conducting further studies to explore how precommitment mechanisms affect exchange outcomes in different environments.
References


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Comparisons and Contributions to Online Communities: A Field Experiment on MovieLens.” *American Economic Review*, September, 100 (4), 1358-98.


**Jurca, Radu, and Boi Faltings.** 2007. “Collusion resistant, incentive compatible


Figure 1. Seller-Buyer game (Auto_fb treatment)

Note: the first number is the buyer’s payoff and the second number is the seller’s payoff.
Figure 2. C10 treatment

Note: the first number is the buyer’s payoff and the second number is the seller’s payoff.
Figure 3. C5 treatment

Note: the first number is the buyer’s payoff and the second number is the seller’s payoff.
Figure 4. C10r5 treatment

Note: the first number is the buyer’s payoff and the second number is the seller’s payoff.
Figure 5. Distribution of sellers’ rebate frequency in the C10r5 treatment
Figure 6. Proportion of sellers who offered rebates over ten rounds
Figure 7. Proportion of efficient trades in each treatment
Table 1  Descriptive summary of the decisions

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Purchasing rate (%)</th>
<th>Buyer Reporting rate*</th>
<th>Seller</th>
<th>Shipping rate*</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Overall (%)</td>
<td>Seller Shipped (%)</td>
<td>Seller did not ship (%)</td>
</tr>
<tr>
<td>Auto_fb</td>
<td>79.17</td>
<td>31.88</td>
<td>28.36</td>
<td>50</td>
</tr>
<tr>
<td>C5</td>
<td>69.57</td>
<td>10.49</td>
<td>3.79</td>
<td>40</td>
</tr>
<tr>
<td>C10</td>
<td>67.50</td>
<td>27.85</td>
<td>26.06</td>
<td>38.71</td>
</tr>
<tr>
<td>C10r5_reb</td>
<td>83.91</td>
<td>26.06</td>
<td>38.71</td>
<td>85.84</td>
</tr>
<tr>
<td>C10r5_noreb</td>
<td>36.14</td>
<td>11.76</td>
<td>61.54</td>
<td>56.67</td>
</tr>
</tbody>
</table>

* The rate is calculated based on the cases where buyers chose to buy.

Note:
Auto_fb: Computer automatic feedback treatment
C5: Feedback cost 5 treatment
C10: Feedback cost 10 treatment
C10r5_reb: the seller provided a rebate in Feedback cost 10 with rebate 5 treatment
C10r5_noreb: the seller did not provide a rebate in Feedback cost 10 with rebate 5 treatment
Table 2. Buyers’ Feedback Reporting Decisions: Random Individual Effect Logit Regression Model

<table>
<thead>
<tr>
<th></th>
<th>Report(_{i,t}) (=1 if report in round (t); =0 if not report)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) (include C5 and C10 treatments)</td>
</tr>
<tr>
<td></td>
<td>Coef. (s.e.)</td>
</tr>
<tr>
<td>Round(_t)</td>
<td>-0.09 (0.07)</td>
</tr>
<tr>
<td>Final round (=1 if (t=10))</td>
<td>-0.56 (0.90)</td>
</tr>
<tr>
<td>C10</td>
<td>-2.45 (0.67)</td>
</tr>
<tr>
<td>C5</td>
<td>-0.55 (0.60)</td>
</tr>
<tr>
<td>C10ship</td>
<td>-5.17 (1.52)</td>
</tr>
<tr>
<td>C10noship</td>
<td>2.82 (1.45)</td>
</tr>
<tr>
<td>C5ship</td>
<td>-0.09 (1.06)</td>
</tr>
<tr>
<td>C5noship</td>
<td>4.85 (1.59)</td>
</tr>
<tr>
<td>C10r5_rebship</td>
<td></td>
</tr>
<tr>
<td>C10r5_norebship</td>
<td></td>
</tr>
<tr>
<td>C10r5_rebnoship</td>
<td></td>
</tr>
<tr>
<td>C10r5_norebnoship</td>
<td></td>
</tr>
<tr>
<td>Wald chi(^2)(-)</td>
<td>30.93</td>
</tr>
<tr>
<td># of obs.</td>
<td>322</td>
</tr>
</tbody>
</table>
Table 3. Buyers’ Purchasing Decisions: Random Individual Effect Logit Regression Model

<table>
<thead>
<tr>
<th></th>
<th>Buy_{i,t} (=1 if purchased in round t; =0 if not)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Include Auto_fb, C5 &amp; C10 treatments (1)</td>
</tr>
<tr>
<td>Round (t)</td>
<td>Coef. (s.e.)</td>
</tr>
<tr>
<td></td>
<td>-0.04 (0.05)</td>
</tr>
<tr>
<td>Final round</td>
<td>Coef. (s.e.)</td>
</tr>
<tr>
<td>(=1, if t=10)</td>
<td>-1.52 (0.42)</td>
</tr>
<tr>
<td>C10</td>
<td>1.77 (0.61)</td>
</tr>
<tr>
<td>C5</td>
<td>1.79 (0.60)</td>
</tr>
<tr>
<td>Auto_fb</td>
<td>2.37 (0.59)</td>
</tr>
<tr>
<td>$\sum_{t=1}^{t-2}$ Postive fb\textsubscript{i,t}</td>
<td>0.12(0.13)</td>
</tr>
<tr>
<td>$\sum_{t=1}^{t-2}$ Negative fb\textsubscript{i,t}</td>
<td>-1.81(0.35)</td>
</tr>
<tr>
<td>Positive $fb_{i,t-1}$</td>
<td>1.56 (0.56)</td>
</tr>
<tr>
<td>Negative $fb_{i,t-1}$</td>
<td>-2.75 (0.65)</td>
</tr>
<tr>
<td>Ship\textsubscript{i,t-1}</td>
<td>1.31 (0.43)</td>
</tr>
<tr>
<td>C10r5_noreb\textsubscript{i,t}</td>
<td>-1.79 (0.87)</td>
</tr>
<tr>
<td>C10r5_reb\textsubscript{i,t}</td>
<td>2.51 (0.80)</td>
</tr>
<tr>
<td>Wald chi2(-)</td>
<td>45.75</td>
</tr>
<tr>
<td># of obs.</td>
<td>710</td>
</tr>
</tbody>
</table>


Table 4. Sellers’ Shipping Decisions: Random Individual Effect Logit Regression Model

| Coef. (s.e.) |  
|-------------|---
| **Ship\(_{i,t}\)** (=1 if shipped the product in round \(t\); =0 if not) |  
| **Random effect Logit regression** |  
| **Include C10, C5 and Auto_fb treatments** |  
| **Coef. (s.e.)** |  
| Round (t) | -0.24 (0.08) |  
| Final round (t=10) | -3.84 (0.83) |  
| C10 | 4.34 (0.92) |  
| C5 | 5.02 (1.02) |  
| Auto_fb | 4.86 (0.93) |  
| Wald chi2(-) | 47.43 |  
| # of obs. | 512 |  

Table 5. Average proportion of efficient trades: OLS Regression Models

<table>
<thead>
<tr>
<th></th>
<th>Avg_Eftrade&lt;sub&gt;i&lt;/sub&gt;</th>
<th>Coef. (s.e.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Include four</td>
<td>Include four treatments</td>
<td></td>
</tr>
<tr>
<td>Coef. (s.e.)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>C10</td>
<td>0.55 (0.05)</td>
<td></td>
</tr>
<tr>
<td>C5</td>
<td>0.58 (0.05)</td>
<td></td>
</tr>
<tr>
<td>Auto_fb</td>
<td>0.70 (0.05)</td>
<td></td>
</tr>
<tr>
<td>C10r5</td>
<td>0.13 (0.22)</td>
<td></td>
</tr>
<tr>
<td>Avg_rebtms&lt;sub&gt;i&lt;/sub&gt;</td>
<td>0.61(0.28)</td>
<td></td>
</tr>
<tr>
<td>R-squared</td>
<td>0.8585</td>
<td></td>
</tr>
<tr>
<td># of obs.</td>
<td>107</td>
<td></td>
</tr>
</tbody>
</table>
Table 6. Average earnings: OLS Regression Models

<table>
<thead>
<tr>
<th>Avg_Earning_i</th>
<th>Buyer</th>
<th>Seller</th>
<th>Coef. (s.e.)</th>
<th>Coef. (s.e.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>C10</td>
<td>39.42 (0.86)</td>
<td>46.38 (0.57)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>C5</td>
<td>39.80 (0.88)</td>
<td>46.57 (0.58)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Auto_fb</td>
<td>43.21 (0.86)</td>
<td>47.79 (0.57)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>C10r5</td>
<td>29.26 (3.63)</td>
<td>43.47 (1.39)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Avg_rebtms_i</td>
<td>13.67 (4.69)</td>
<td>3.73 (1.72)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R-squared</td>
<td>0.9898</td>
<td>0.9966</td>
<td></td>
<td></td>
</tr>
<tr>
<td># of obs.</td>
<td>107</td>
<td>107</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Appendix A: Proof of proposition 1

Proof.

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.

In a complete information market, if the bad seller chooses $(e(0), e(0))$, buyer $i$ will buy in period 1 if $\mu_0^i \geq (P - \beta)/(\alpha - \beta)$ but not in period 2 (since the seller does not make effort in period 1). So, the seller's total expected payoff over the two periods is $EU_s = E(f(\mu_0^i) \cdot P) = P \cdot E(f(\mu_0^i)) = f(\mu_0^i)P$.

If he chooses $(e(1), e(0))$, the buyer will buy in period 1 and 2. So the seller's total expected payoff is:

$$EU_s = E[\Pr(sale)_1 P - e(1) + \delta \Pr(sale)_2 P] = E[f(\mu_0^i + (1 - \mu_0^i)\hat{e}_1)P - e(1) + \delta f(\mu_0^i)P],$$

where $\delta$ is a discount factor to transform the future payoff to the present value. If $\hat{e}_1 = 1$, then $EU_s = E[P - e(1) + \delta f(\mu_0^i)P] = P - e(1) + \delta f(\mu_0^i)P$. If $P - e(1) + \delta f(\mu_0^i)P \geq f(\mu_0^i)P$, i.e., $e(1) \leq [1 - (1 - \delta)f(\mu_0^i)]P$, 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 expected payoffs to bad type sellers in each period are the following:

At $t=1$, $V_1 = E[\Pr(sale)_1 P + \delta l(e_1)V_2 - e_1(1)]$

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

If $e_1 = 0$, $l(e_1) = 0$, and $V_1 = E[\Pr(sale)_1 P] = E[f(\mu_0^i + (1 - \mu_0^i)\hat{e}_1)P] = E[f(\mu_0^i)P] = f(\mu_0^i)P$.

At $t=2$, $V_2 = E[\Pr(sale)_2 P + \delta l(e_2)V_3 - e_2(1)]$
If $e_2 = 1$, $I(e_2) = 1$, and $V_2 = P + \delta V_3 - e(1)$.

If $e_2 = 0$, $I(e_2) = 0$, and $V_2 = E[Pr(sale)_2 P] = E[f(\mu_1^I + (1 - \mu_1^I)\hat{e}_2)P] = E(f(\mu_1^I)P) = E(f(\mu_0^I)P) = f(\mu_0)P$

At $t=T-1$, $V_{T-1} = E[Pr(sale)_{T-1} P + \delta I(e_{T-1})V_T - e_{T-1}(1)]$

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

If $e_{T-1} = 0$, $I(e_{T-1}) = 0$, and $V_{T-1} = E[Pr(sale)_{T-1} P] = f(\mu_0)P$

At $t=T$, $V_T = E[Pr(sale)_T P] = f(\mu_0)P$.

To induce the bad sellers to choose $e_t = 1$ for every period prior to $T$, the condition $e(1) \leq [1 - (1 - \delta)f(\mu_0)]P$ must be satisfied. As long as it holds, bad sellers will make a genuine effort for $t=0$ to $t=T-1$, but will cease to do so in the last period. ■

Appendix B: Proof of Proposition 2

Proof.

If the reporting cost is more than the maximum reporting benefit, then no buyer will be inclined to report. In this case, the seller’s expected payoff is $f(\mu_0)P$. The good sellers will be worse off than in the case where there is no reporting cost, and the bad sellers will not make an effort in any period. When the rebate mechanism is introduced and the amount of rebate is enough to cover some buyers’ reporting costs, some buyers are willing to report when provided a rebate. We assume that all buyers report honestly if they decide to report. If a bad seller provides the rebate but does not make an effort, he knows, as long as at least one buyer reports negative feedback, his type will be revealed. The reason is that good sellers always make an effort to provide good transactions and only bad sellers strategically choose whether to make an effort.
Therefore, if a bad seller decides to provide a rebate, his effort decisions will be the same as in the complete information case discussed in Proposition 1. Since in this case, \( e(1) \leq [1 - (1 - \delta) f(|\mu|)]P \) is always true, a bad seller will make a genuine effort from \( t=1 \) to \( t=T-1 \), but will cease to do so in the last period.

We next show that when we introduce a rebate mechanism, there is a pooling equilibrium where both types of sellers will choose to give rebates if the rebate is less than the expected payoff of having a good reputation minus the expected payoff when there is no reputation information in the market at all, i.e.,
\[
r < E[\Pr(sale)_{T-1} P + \delta l(e_{T-1}) V_{T} - e_{T-1}(1)] - f(|\mu|)P.
\]
In the equilibrium we derived in appendix A, \( \Pr(sale)_{T-1} = 1, l(e_{T-1}) = 1, V_{T} = f(|\mu|)P \), and \( e_{T-1}(1) = e(1) \), the above condition is simplified to
\[
r < [1 - (1 - \delta) f(|\mu|)]P - e(1). \]
The reason for the pooling equilibrium is the following: given the off-equilibrium path belief that anyone who chooses not to provide rebates must be a bad seller, if good sellers choose the rebate option but bad sellers do not, then buyers can immediately identify bad sellers by observing which ones do not provide rebates. Therefore, bad sellers have an incentive to mimic good sellers by providing rebates if the expected payoff of doing so is higher than the expected payoff of not doing so — i.e., \( r < [1 - (1 - \delta) f(|\mu|)]P - e(1) \). Since we assume that the good sellers’ effort cost is 0, good sellers will always provide rebates and make an effort if \( r < [1 - (1 - \delta) f(|\mu|)]P \). Thus,

(1) if \( r < [1 - (1 - \delta) f(|\mu|)]P - e(1) \), both bad and good sellers will provide rebates;

(2) if \( [1 - (1 - \delta) f(|\mu|)]P - e(1) < r < [1 - (1 - \delta) f(|\mu|)]P \), only good sellers will provide rebates; and

(3) if \( r > [1 - (1 - \delta) f(|\mu|)]P \), neither good sellers nor bad sellers will give rebates.

As we mentioned above, in the last round, bad sellers will not make an effort. Expecting this, buyers will decide whether to buy according to their initial beliefs. In
a listed-price market where the rebate is less than the price $P$, offering a rebate in the last period will not make a bad seller worse than not doing so, since he will not lose the rebate if no one buys from him in the last period. ■

Appendix C: An Adverse Selection Model

To understand the intuitions behind the rebate mechanism, we use a simple setup of a pure adverse selection model with infinite periods. The basic setup is similar to the mixed model of both adverse selection and moral hazard discussed in Section II, except that sellers’ cannot take actions to affect the transaction outcomes in the pure adverse selection model. The transaction outcomes are solely determined by nature according to the seller’s type.

If a seller's complete past reputation history is available to buyers, then a buyer can update her belief by using the information. Buyer $i$’s belief of meeting a good seller in period $t$ is

$$
\mu^i_{t-1} = \mu^i_{t+1} + t_{GR} + t_{BR} = \frac{\mu^i_{t} \cdot \alpha^{(1-\alpha)^i \cdot t_{BR}}}{\mu^i_{t} \cdot \alpha^{(1-\alpha)^i \cdot t_{BR}} + (1-\mu^i_{t}) \cdot \beta^{(1-\beta) \cdot t_{BR}}},
$$

where $t_{GR}$ and $t_{BR}$ represent the number of good and bad reports the seller received in the past, respectively. A seller’s expected payoff at period $t$ is

$$
EU_{st} = Pr \left( \mu^i_{t} \geq \frac{P-\beta}{\alpha-\beta} \right) \cdot P = f(\mu^i_{t}) \cdot P.
$$

In the first round, a buyer whose initial belief $\mu^i_{0}$ is less than $\frac{P-\beta}{\alpha-\beta}$ does not buy. In the second round, after the buyer observes sellers’ reputations, the buyer updates her belief and decides whether to buy based on the value of $\mu^i_{t} \cdot \alpha + (1-\mu^i_{t}) \cdot \beta$ and $P$. If a seller earns a good (or bad) reputation in period 1, then in period 2 there will be more (or fewer) buyers whose updated belief is that $\mu^i_{t}$ is greater than $\frac{P-\beta}{\alpha-\beta}$. Since good sellers have a higher probability of shipping than bad sellers, in the long run, as $t$ goes to infinity, $\mu^i_{t} = 1$ with high probability for a good seller and $\mu^i_{t} = 0$ with high
probability for a bad seller.\textsuperscript{25} Therefore, in the long run, when a seller’s complete reputation is revealed, a good seller has a higher probability of selling than a bad seller.

When there is no information available, only optimistic buyers whose prior belief was $\mu_0^i \geq \frac{p-\beta}{\alpha-\beta}$ will buy. If the true proportion of good sellers in the market is less than $\frac{p-\beta}{\alpha-\beta}$, then optimist buyers will be better off not buying. If the true proportion of good sellers in the market is greater than $\frac{p-\beta}{\alpha-\beta}$, then pessimistic buyers whose prior belief is $\mu_0^i < \frac{p-\beta}{\alpha-\beta}$ will be better off buying. When there is complete information, buyers’ purchasing decisions will depend on their updated beliefs about $\mu_{t-1}$. If $\mu_{t-1}$ goes up (or down) so that the value of $\mu_{t-1} \alpha + (1 - \mu_{t-1}) \beta$ is more (or less) than $P$, then the buyer will buy (or not buy). Compared with the no-information case, the total buyers’ welfare increases when there is complete information. When changing from the no-information case to the complete information case, there is a wealth transfer from bad sellers to good sellers because buyers can identify sellers’ types in the complete information case.

If there is a positive reporting cost for all buyers, say $C$, then future buyers may not update their beliefs correctly. To see this, suppose that buyers’ internal reporting benefit is $b \in [0,B]$. If the reporting cost $C$ is higher than the maximum reporting benefit $B$ for all buyers, then no buyer reports.

If $C < B$, we consider two cases. In the first case, if the benefits from giving good reports and bad reports are not symmetric, then good reports and bad reports will not be systematically revealed. If, for example, 60% of all good reports are revealed, but only 10% of all bad reports are revealed, then the observed feedback is biased towards the positive. When the observed good and bad reports do not correctly represent the

\textsuperscript{25} Proof is provided in the Appendix D.
correct distribution of positive and negative transactions in the market, future buyers cannot update their beliefs correctly. Therefore, buyers’ propensities to buy depend only on the initial prior belief \( \mu_0 \) and price \( P \). In essence, it is the same as the case where no information is available.

In the second case, if the reporting benefits from giving good reports and bad reports are symmetric, then good reports and bad reports will be systematically revealed. Future buyers can update their beliefs correctly, but at a slower rate than in the case where all buyers report.\(^{26}\) It takes longer for buyers to learn a seller’s type in this case than in the complete information case.

The problem of missing feedback reports caused by reporting costs can be overcome by the following simple mechanism. The market maker provides sellers an option to provide rebates (not necessarily in monetary form) contingent on buyers’ leaving feedback, regardless of whether the feedback is positive or negative.

Proposition 3. If the rebate \( r \leq \alpha - f(\mu_0)P \) and \( r < f(\mu_0)P - \beta \), there exists an equilibrium where good sellers always provide rebates and bad sellers mimic good sellers by providing rebates even after their bad types are identified through the reports and it is no longer profitable to mimic good sellers, given the off-equilibrium path belief that anyone who chooses not to rebate must be a bad seller. If the rebate \( r > \alpha - f(\mu_0)P \), then both types of sellers will choose not to offer rebates, \( NRs \).

\(^{26}\) It is easy to illustrate this with examples. Consider a case where it is commonly know that \( \alpha=0.8 \), \( \beta=0.3 \). Suppose a good seller shipped products 8 out of the first 10 periods and the 11th buyer’s prior belief is \( \mu_0=0.5 \). If the seller’s past reputation history is fully revealed, then the 11th buyer’s updated belief of the seller’s type being good is \( \frac{0.5 \times 0.8^8(1-0.8)^2}{0.5 \times 0.8^8(1-0.8)^2 + 0.5 \times 0.3^8(1-0.3)^2} = 0.99 \). However, if the seller’s past positive and negative feedback are symmetrically revealed half of the time, then the 11th buyer’s updated belief is only \( \frac{0.5 \times 0.8^8(1-0.8)^4}{0.5 \times 0.8^8(1-0.8)^4 + 0.5 \times 0.3^8(1-0.3)^2} = 0.93 \). Please note that a good seller may not necessarily ship the products 8 out of every 10 times.
The intuition is as follows: if good sellers choose the rebate option but bad sellers do not, then buyers can immediately identify sellers' types by observing who provides rebates. Therefore, bad sellers will mimic good sellers in the early periods. Since both types of sellers provide rebates to overcome buyers' reporting costs, buyers will report. We assume that all buyers report honestly if they decide to report. Thus, a bad seller's type will be revealed through feedback reports. In the long run, even if a bad seller's type is revealed, he may keep on choosing the rebates. The reason is that if a buyer identifies a bad seller, she would not buy from him. Therefore, even if a bad seller chooses the rebate, he does not need to pay for the rebate. This pooling equilibrium still holds when we combine moral hazard with the adverse selection model.

**Proof of Proposition 3:**

*Proof.*

First, let's examine the separating equilibrium where good sellers choose rebates \((Rs)\), and bad sellers choose no rebates \((NRs)\). 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 he is a good seller, and the good seller's payoff is \(\alpha - r\). If a seller does not choose the rebate option, then he is considered a bad seller; the buyer's willingness to pay to a bad seller is \(\beta\), so the seller's payoff is \(\beta\). If the rebate is larger than the price difference between good and bad sellers, i.e., \(r > \alpha - \beta\) then both good and bad sellers choose not to rebate \((NRs)\). If the rebate is less than the price difference between good and bad sellers, i.e., \(r \leq \alpha - \beta\), we need to check whether any sellers want to deviate from the separating equilibrium. A bad seller would get the higher payoff \(\alpha - r\) instead of \(\beta\) if he pretends to be a good seller by choosing the rebate option. Thus, the separating equilibrium does not exist.

Nor does there exist another separating equilibrium, where good sellers choose not to rebate and bad sellers choose to rebate. The payoff to the good seller is \(\alpha\), the payoff
to the bad seller is $\beta - r$, and $\alpha > \beta$, so that the bad seller can have a higher payoff if he presents himself as a good seller by choosing a rebate. The bad sellers have incentives to deviate from this separating equilibrium. Thus, the separating equilibrium does not exist, either.

Since the separating equilibrium does not exist, we next examine the pool equilibrium. First, we examine the pooling equilibrium where both types of sellers choose to provide rebates, $R_s$. The rebate $r$ is chosen in a form that can systematically reveal good and bad reporting.\(^{27}\) To simplify the analysis, we assume that $r$ is greater than the net reporting cost (i.e., $C - B$), so it will reveal all reports.\(^{28}\) In this case, buyers cannot know a seller’s type just by observing the seller’s choice about providing rebates. However, since both types of sellers provide rebates, all buyers will provide reports. A future buyer can, by using the information about a seller’s previous history, update her beliefs on the seller's type. If buyer $i$ does not report, her expected utility at period $t+1$ is

\[
EU_{b,t+1}^i = \mu_t^i \alpha + (1 - \mu_t^i) \beta - P, \tag{1}
\]

while if she chooses to report, her expected utility is

\[
EU_{b,t+1}^i = \mu_t^i \alpha + (1 - \mu_t^i) \beta - P - C + B + r. \tag{2}
\]

In this case, $r$ is greater than the net reporting benefit, so a buyer has higher expected payoff if she chooses to report. The expected payoff for the seller at period $t+1$ is

\[
EU_{s,t+1}(Rs; \text{if buyer chooses GR or BR}) = Pr \left( \mu_t^i \geq \frac{p-\beta}{a-\beta} \right) P - r = f(\mu_t^i)P - r. \tag{3}
\]

\(^{27}\) The form of rebate depends on what causes no reports or no systematic reports. In this paper, we use monetary form for the rebates. See Li (2010a) for more discussion.

\(^{28}\) If $r$ is not greater for all buyers’ net reporting cost, some buyers will report. As long as good and bad reports are systematically revealed, future buyers will still be able to update their beliefs in the right direction, and at a slower rate than in the case where all buyers report as shown in footnote 26. The general results still hold.
As the number of time periods $t$ becomes infinite, according to the Weak Law of Large Numbers, $\mu$ for the good seller equals 1 with very high probability, and the buyer's willingness to pay converges to $\alpha$; $\mu$ for the bad seller equals 0 with very high probability, and the buyer's willingness to pay converges to $\beta$. If the expected payoff from providing rebates is higher than the expected payoff from not providing rebates in the long run, i.e., $\alpha - \mu \geq f(\mu_0)P$, then the good seller will choose to provide the rebate if he is patient. If the expected payoff from providing the rebate is higher than the expected payoff from not providing at the beginning, i.e., $f(\mu_0)P - r > \beta$, then the bad seller wants to mimic the good seller. In the long run, even when a bad seller’s type is revealed i.e., $f(\mu_t)P - r < \beta$, he may continue to choose the rebates. The reason is that if a buyer identifies a bad seller, the buyer would choose not to buy from the seller. Therefore, the bad seller does not need to pay for the rebate. So as long as $r \leq \alpha - f(\mu_0)P$ and $r < f(\mu_0)P - \beta$, the patient good sellers will choose to give the rebate, and the patient bad sellers will also give the rebate. If $r > \alpha - f(\mu_0)P$, both types of sellers will choose no rebate, $NRs$.

Another pooling equilibrium is that both types of sellers choose not to rebate, $(NRs)$, supported by the off-equilibrium path belief that anyone who chooses to rebate, $Rs$, must be a bad seller. In this case, the seller's expected payoff is $f(\mu_0)P$ for every period.

If $r \leq \alpha - f(\mu_0)P$, 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 any sellers who chooses to rebate are bad, is not feasible. If $r > \alpha - f(\mu_0)P$, then the pooling equilibrium in which both types of sellers choose no rebate, $NRs$, exists. ■

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29 This result is different than the result in the auction market case as shown in Li (2010a) where a bad seller will no longer give a rebate after his type is revealed through reports.
Appendix D: Proof of footnote 25

Proof.

For each history \( h_t \) of feedback history, buyers use Bayes’ rule to update their beliefs about sellers’ types when there are complete histories about the sellers,

\[
\mu_t(\theta_G | h_t) = \frac{\mu_{t-1} e_{GR}(1-\alpha)^{tBR}}{\mu_{t-1} e_{GR}(1-\alpha)^{tBR} + (1-\mu_{t-1}) e_{BR}(1-\beta)^{tBR}}
\]

We can rewrite this equation as the following:

\[
\frac{1}{1 + \frac{\mu_{t-1}}{\mu_{t}} \left( \frac{\beta}{\alpha} \right)^{\frac{t_{GR}}{t}} \left( \frac{1-\beta}{1-\alpha} \right)^{\frac{t_{BR}}{t}}}.
\]

If the seller is of type \( \theta_G \), then the Weak Law of Large Numbers implies that

\[
\text{Prob} \left( \frac{\tilde{t}_{GR}}{t} \approx \alpha \right) \approx 1.
\]

When \( t \) is large, where \( \tilde{t}_{GR} \) is a random variable that records the number of good reports up to and including period \( t \). If \( \frac{\tilde{t}_{GR}}{t} \approx \alpha \), then

\[
\left( \frac{\beta}{\alpha} \right)^{\frac{t_{GR}}{t}} \left( \frac{1-\beta}{1-\alpha} \right)^{\frac{t_{BR}}{t}} \approx \left( \frac{\beta}{\alpha} \right)^{\alpha} \left( \frac{1-\beta}{1-\alpha} \right)^{1-\alpha}.
\]

Therefore

\[
\ln \left[ \left( \frac{\beta}{\alpha} \right)^{\alpha} \left( \frac{1-\beta}{1-\alpha} \right)^{1-\alpha} \right] = \alpha \ln \left( \frac{\beta}{\alpha} \right) + (1-\alpha) \ln \left( \frac{1-\beta}{1-\alpha} \right) < \ln(\beta + 1 - \beta) = 0,
\]

and it follows that \( \left( \frac{\beta}{\alpha} \right)^{\alpha} \left( \frac{1-\beta}{1-\alpha} \right)^{1-\alpha} < 1 \). Consequently, for large \( t \), we conclude that

\[
\frac{1}{1 + \frac{\mu_{t-1}}{\mu_{t}} \left( \frac{\beta}{\alpha} \right)^{\frac{t_{GR}}{t}} \left( \frac{1-\beta}{1-\alpha} \right)^{\frac{t_{BR}}{t}}} \approx \frac{1}{1 + \frac{\mu_{t-1}}{\mu_{t}} \left( \frac{\beta}{\alpha} \right)^{\alpha} \left( \frac{1-\beta}{1-\alpha} \right)^{1-\alpha}} \approx \frac{1}{1+0} = 1.
\]

with high probability. A similar argument established that \( \mu_t(\theta_B | h_t) \approx 0 \) with high probability when the seller is of type \( \theta_B \) and \( t \) is large. □