A Dollar for Your Thoughts: Feedback-Conditional Rebates on eBay

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Abstract. We run a series of controlled field experiments on eBay where buyers are rewarded for providing feedback. Our results provide little support for the hypothesis of buyer's rational economic behavior: the likelihood of feedback barely increases as we increase feedback rebate values; also, the speed of feedback, bid levels and the number of bids are all insensitive to rebate values.

By contrast, we find evidence consistent with reciprocal buyer behavior. Lower transaction quality leads to a higher probability of negative feedback as well as a speeding up of such negative feedback. However, when transaction quality is low (as measured by slow shipping), offering a rebate significantly decreases the likelihood of negative feedback.

All in all, our results are consistent with the hypothesis that buyers reciprocate the seller's "good deeds" (feedback rebate, high transaction quality) with more frequent and more favorable feedback. As a result, sellers can "buy" feedback, but such feedback is likely to be biased.

Key words: feedback, rebates, field experiment

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1. Introduction

Studies of eBay buyer behavior have shown that a seller's past experience, as measured by the number and quality of past feedback postings, is an important determinant of a seller's success, both in terms of number of bidders and size of bids (Cabral, 2012). This is important for the seller, insofar as better reputation leads to greater sales; it is also important for the platform owner, to the extent that better information leads to more sales, which in turn lead to higher revenues from selling fees. All in all, customer feedback is an important component of a firm's strategy, be it a seller or an intermediary.

In this paper, we consider one possible seller strategy for eliciting buyer feedback: to provide buyers with a rebate conditional on rating the quality of their transaction. The rebate will be provided as long as a feedback rating is left, regardless of whether the feedback is positive or negative.[1] By establishing two eBay sellers who auction the same homogeneous good (a USB pen drive), we are able to run a series of controlled field experiments where we vary the degree to which buyers are rewarded for feedback, as well as a component of transaction quality (speed of shipment).

Our experiment is motivated by a series of theoretical hypotheses derived from two paradigms of buyer behavior. A first one, which we refer to as the *homo economicus* paradigm, implies that buyers are more likely to provide feedback when feedback is rewarded; do so quicker; and bid higher in anticipation of a feedback reward. A second paradigm, which we refer to as *homo reciprocus*, implies that buyers are more likely to give favorable feedback (less negative, more positive) when sellers offer a feedback rebate or higher transaction quality.

Our field experiment addresses these and other related questions. We find relatively little evidence for the *homo economicus* paradigm: the likelihood of feedback increases marginally as we increase feedback rebate values; the speed of feedback seems relatively insensitive to the size of the feedback rebate; and so are bid levels and the number of bids.

By contrast, we find fairly strong evidence consistent with the *homo reciprocus* paradigm. In particular, we find that when transaction quality is low (as measured by shipment delay), offering a rebate decreases the likelihood of a negative feedback message. We also find that lowering transaction quality leads to a higher probability of negative feedback as well as a speeding up of such negative feedback. All of these results are consistent with the general hypothesis that buyers reciprocate the seller's "good deeds" (feedback rebate, high transaction quality) with more frequent, more favorable feedback.

In sum, our results suggest that a seller can buy himself more buyer feedback, but such feedback is likely to be biased, even though the rebate is provided regardless of whether the feedback is positive or negative. By contrast, contrary to economic theory predictions, we show that feedback rewards have no effect on bidding behavior, either the number of bidders or the average bid. This can be explained by buyer myopia, inattention, or incredulity with respect to the seller's feedback reward offer. It also suggests that the cost of obtaining more customer feedback is greater than a rational, forward looking model would predict.

Our focus on feedback bias may seem misplaced: if sellers can get more positive feedback by offering feedback rewards, then that's all that matters, one might argue. We reply to that objection in two ways. First, while the "direct" effect of positive feedback is clearly positive, to the extent that inaccurate feedback may reduce buyer's confidence, sellers may

1. In other words, the rebate is unbiased because it is not offered for one type of feedback only.

also be harmed by biased feedback. If only one seller offers feedback rebates, this effect is unlikely to be very important. However, in a situation where feedback rebates are more general, the cost of inaccurate feedback may be significant.

This leads us to the second point: from the perspective of a platform owner (e.g., eBay or TaoBao), feedback bias matters: if feedback is not accurate, then the value of the feedback system is lower, and so is buyer's trust.[2] Our results cannot directly address the effect of a system-wide feedback rebate; this would require eBay itself to run the field experiment. In this sense, our approach is a second best. Still, we believe our results shed some light on how buyers respond to a rebate mechanism.

More generally, our results point to the potential negative effect of reciprocity. Buyers may be "too good for their own good," as it were: in their eagerness to reciprocate an act of kindness (feedback rebate) they treat the seller better than the transaction quality justifies it, thus contributing to the lowering of the overall value of the feedback system, which in the process may harm buyers, the platform owner — and possibly even sellers.

■ **Related Literature.** A growing theoretical and empirical literature shows that a seller's reputation history is an important determinant of a seller's success, especially in online markets.[3] In online markets, reputation systems usually rely on voluntary feedback from the parties involved. This creates a problem of public good under-provision, for which various solutions have been proposed. For example, Miller et al (2005) and Jurca and Faltings (2007) propose truth-eliciting incentive schemes to induce buyers to report and do so honestly. These mechanisms either require buyers or the market-maker (e.g., eBay) to bear the reporting cost. Given the importance of customer feedback, sellers have an interest in encouraging buyers to post a review, so sellers may have more incentive to bear the reporting cost than buyers or the market.

Addressing the issue of incentive provision, Li (2010a) proposes and theoretically analyzes a rebate mechanism in an online auction market: sellers have the option of committing by providing a rebate (not necessarily in monetary form) to cover the buyer's reporting cost, regardless of whether the feedback is positive or negative. In theory, this rebate mechanism plays the dual role of incentivizing buyers to leave feedback and providing a device for sellers to signal quality or effort to cooperate. In equilibrium, buyers avoid sellers who do not choose the rebate option and incorporate the rebate amount into their bids.

Although providing monetary incentives is not the only way of inducing the desired buyer behavior, it is still one of the easier strategies for sellers to implement.[4] Using monetary rebates as incentives for feedback, Li and Xiao (forthcoming) conduct a laboratory

2. To be fair, if bias is systematic (i.e., every seller's feedback is inflated by the same level) then the loss in informational value may not be very high. However, it is possible that greater bias is also associated with noisier feedback (this will be the case if feedback inflation levels vary across sellers).
3. See Shapiro (1983), Avery et al (1999), Dellarocas (2003), Bolton et al (2004), Houser and Wooders (2006), Jin and Kato (2006), Resnick et al (2006), Cabral and Hortaçsu (2010), Grosskopf and Sarin (2010).
4. For instance, Abeler et al (2010) find that apology is more effective than monetary incentives in making buyers withdraw their negative feedback on eBay. Chen et al (2010a) run a field experiment on MovieLens.com and find that effective personalized social information can increase the level of public goods provision. Using data from a major online travel agency in China, Gu and Ye (2012) study how the online management responses affect customers' feedback. Alternative ways of motivating agents are also explored in the work of Bénabou and Tirole (2003), Ariely et al (2009), Chen at al (2010b), and Wang (2010).

experiment to examine the effect of the rebate mechanism on market efficiency in a listed-price market.[5] They find that a seller's rebate offer increases the buyers' propensity to report in good transactions but not in bad transactions; market efficiency under the rebate mechanism increases with the probability that sellers will provide a rebate; and the dollar rebate does not affect the honesty of the feedback reports.

In this paper, we run a field experiment on eBay to test one possible seller strategy: to provide buyers with a monetary rebate conditional on rating the quality of their transaction. We are interested in investigating whether paying for feedback induces buyers to give more feedback, whether buyers bid higher when there is a rebate, and most important, whether the nature of buyer feedback is altered by the fact a monetary reward is offered by the seller. This is a natural next step with respect to Li (2010a), a theory paper, and Li and Xiao (forthcoming), a laboratory experiment paper. With respect to laboratory experiments, field experiments have the virtue of applying to a real-world situation rather than a laboratory setting. Compared to other field experiments such as Abeler et al (2010), this paper tests a mechanism hitherto not considered (in field experiments), namely conditional rebates.

■ **Road map.** The paper is organized as follows. Section 2 derives theoretical predictions in the form of testable hypotheses. In Section 3, we describe the experimental design. The results are presented in Section 4, which includes both basic tabulations and regression results. Finally, Section 5 concludes the paper.

2. Theory and hypotheses

Economics and psychology provide behavioral paradigms with specific predictions regarding bidding and feedback patterns. In this section, we consider two stylized models corresponding to the paradigms of economic rationality and reciprocal behavior: *homo economicus* (HE) and *homo reciprocus* (HR). We should state from the outset that the two models below are not mutually exclusive. In fact, our prior is that actual observed behavior will feature a little bit of each model.

Let us first consider the paradigm most closely related to economic rationality, *homo economicus*. This paradigm postulates that buyers make choices so as to maximize utility net of monetary and transactions costs. Suppose that giving feedback implies a cost c, where c is buyer specific (and possibly time specific as well, as we will consider later). Then we would expect the buyer to provide feedback if and only if $r > c$, where r is the rebate value. It follows that

HE1. *The likelihood that feedback is given is increasing in rebate value.*

Regarding the nature of the feedback, economic rationality has little to say. One possibility is that the buyer gives random feedback. Another possibility is that the buyer gives true feedback, that is, feedback that accurately corresponds to the quality of the transaction.[6] Either way, as far as economic rationality is concerned, the nature of feedback should

5. In Li and Xiao (forthcoming), market efficiency is measured by number of efficient trades (i.e., the case where the buyer bought and the seller shipped the product) as well as earnings of buyers and sellers for each treatment.

6. This is the assumption made by Cabral and Hortacsu (2010), for example.

be uncorrelated with the rebate value.

Suppose that the buyer's cost of providing feedback is time dependent and given by c_t, which follows some stochastic process. A rational buyer will then implement an optimal stopping time at which to give feedback. In this context, a higher value of r implies not only a higher likelihood of feedback (at some point) but also an earlier stopping time. Specifically,

HE2. *The delay between delivery time and feedback time is decreasing in rebate value.*

Finally, the economic rationality approach also has something to say about bidding behavior. Since conditional rebates are announced before the auction takes place, a rational bidder anticipates that, should she place the highest bid and win the auction in question, she will have the option of receiving a feedback rebate. This option is worth

$$z(r) = \max\{r - \min\{c_t\}_{t=0}^{T}\}$$

where T is the number of days when feedback can be given. Assuming that the ex-ante distribution of values of c_t is sufficiently dispersed, we have $0 < z(r) < r$. It follows that an economically rational bidder should anticipate this option and increase her bid by an amount $z(r)$. Noting that $z(r)$ is increasing in r, this implies that bids should be increasing in r. To the extent that there is an auction entry cost that varies from bidder to bidder, the above argument also implies that the number of bidders should be increasing in r.

HE3. *Bid values and the number of bidders are increasing in rebate value.*

We now turn to the reciprocal behavior paradigm. It has been theorized and tested (both in the laboratory and on the field) that reciprocity plays an important role in human behavior.[7] In the present context, we propose a simple model of feedback behavior that incorporates this behavioral pattern. The main building block is the assumption that buyers receive utility from giving feedback and that this utility is a function of transaction quality as well as the rebate value. The idea is that the quality of a transaction as well as the feedback rebate are seen as "gifts" by the seller, whereas feedback is the buyer's way to reciprocate such gifts.

Specifically, we assume that the buyer receives utility u_P and u_N from giving positive and negative feedback, respectively, where

$$\begin{aligned} u_P &= \alpha_0\,(q - \bar{q}) + \beta_0\, r - c \\ u_N &= \alpha_1\,(\bar{q} - q) - \beta_1\, r - c \end{aligned} \tag{1}$$

where α_i, β_i are parameters, q is transaction quality, $\bar{q}$ a reference quality level, r the rebate level and c the cost of giving feedback. The idea is that q and r are "good deeds" done by the seller to the buyer. The more of these good deeds the buyer receives, the more she is

7. For example, Fehr et al. (1993) test a gift-exchange game in the laboratory and find that higher wages offered by an employer lead to considerably more effort provision (where effort is costly). In a field experiment, Gneezy and List (2006) find that positive reciprocity vanishes over time. Also in a field experiment, Falk (2007) finds that the relative frequency of donations increases by 17 percent if a small gift is provided to potential donors (75 percent for a large gift). The role of reciprocity is also explored in the work of Fehr and Gächter (2000b) and Dellarocas and Wood (2008).

willing to reciprocate with a "good" act, namely a positive feedback message; and the less she is willing to reciprocate with a "bad" act, namely a negative feedback message. Finally, the buyer receives $u_\emptyset = 0$ from not giving any feedback.

A *homo reciprocus* chooses action x that maximizes u_x, where $x \in \{P, N, \emptyset\}$. Specifically, an *homo reciprocus* follows the feedback procedure

$$\begin{array}{lll} \text{positive feedback} & \text{if} \quad u_P > u_N & u_P > 0 \\ \text{negative feedback} & \text{if} \quad u_N > u_P & u_N > 0 \\ \text{no feedback} & \text{if} \quad u_P < 0 & u_N < 0 \end{array} \tag{2}$$

In this context, an increase in r has an ambiguous effect on the probability of (some) feedback: on the one hand, it increases u_P, and so increases the probability of positive feedback; on the other hand it decreases u_N, and so decreases the probability of negative feedback.

While it is not possible to make a clear prediction regarding the likelihood of feedback, the *homo reciprocus* model implies a clear prediction regarding the nature of feedback. Since u_P is increasing in r and u_N is decreasing in r, we have

HR1. *The* relative *likelihood of negative feedback with respect to positive feedback is decreasing in r.*

So far we have considered the effects of a higher reward for feedback. As mentioned earlier, in our field experiment we also control for transaction quality q, in the form of fast or slow shipping time. From (2), we see that a lower value of q increases u_N and decreases u_P. This implies

HR2. *The* relative *likelihood of negative feedback with respect to positive feedback is higher when transaction quality is lower.*

As to the speed of feedback, the *homo reciprocus* model is as ambiguous as it is regarding the probability of some feedback. When the reward for feedback is increased, we expect positive feedback to arrive earlier and negative feedback to arrive later, but there is no clear prediction regarding the arrival of some feedback.

Regarding transaction quality, (2) implies that a decrease in q leads to an increase in u_N, which by (2) implies an increase in the likelihood of negative feedback. We single out this prediction because previous literature has shown that there is such a thing as "demand for justice."[8] In the present context, this implies that the coefficient α_1 is particularly high: if buyers feel that they were poorly treated in the transaction (low q), then they get a high utility from reciprocating such bad behavior, and do so by providing negative feedback. In addition to HR2 (negative feedback is more likely) we also expect a speeding up of such negative feedback.

HR3. *Lower transaction quality leads to faster arrival of feedback.*

Finally, we note that, regarding bidding behavior, the reciprocity model is silent, that

8. See for example, Brandts and Charness (2003); Charness and Levine (2007); de Quervain et al (2004); Fehr and Gächter (2000a); and Xiao and Houser (2005).

Table 1
Summary of theoretical hypotheses regarding the effect of an increase in conditional feedback rebate

	Rational	Reciprocal
Increase in rebate value		
Probability of feedback	+	
Nature of feedback (N/P)		−
Speed of feedback	+	
Bid level	+	
Decrease in transaction quality		
Nature of feedback (N/P)		+
Speed of negative feedback		+

is, implies no specific prediction (unlike the economic rationality model, which, as we saw earlier, predicts higher bids and number of bidders).

Table 1 summarizes the main theory predictions in terms of the effect of an increase in conditional feedback rebate as well as a decrease in transaction quality, the two control variables we use in our field experiment. The two rightmost columns correspond to the two paradigms we consider, economic rationality and reciprocal behavior. A "+" (resp. "−") sign represents a positive (resp. negative) effect of a change in the control variable (feedback rebate increase, transaction quality decrease).[9] A blank cell signifies that the paradigm in question implies no particular prediction. From Table 1, we see that the HE and HR paradigms are not necessarily incompatible. In fact, we would expect reality to be a combination of both paradigms: we also have economic sense as well as a sense of reciprocity. Still, an interesting question is the relative importance of each paradigm. We next turn to the testing of our theoretical hypotheses.

3. Field experiment design

To examine the effects of monetary rebates on feedback behavior, we sold new Kingston 2GB USB pen drives on eBay (Figure 1). We chose to sell this particular product because it is a relatively standard product and it is sold by several other sellers.[10] We chose to conduct the field experiment on eBay because it is the world's largest online auction market and has been the object of numerous complementary studies and experiments.[11]

We registered two IDs on eBay and accumulated 75 positive feedback scores on each ID from buying and selling the Kingston pen drive. In this way, before beginning our experiment, we had two sellers with similar, established records. So as to avoid being

9. In Table 1, "Nature of feedback" refers to the relative weight of positive and negative feedback, whereas speed of feedback refers to an inverse measure of the number of days until the buyer provides feedback.
10. One difficulty we experienced was that Kingston stopped producing the 2GB USB drives halfway through our experiment. We tried the best we could to purchase the same model USB drives around the world so as to continue selling the same object.
11. See for example Dellarocas and Wood (2008); Brown and Morgan (2006); Resnick et al (2006); Brown et al (2010); Li (2010b).

Figure 1
Kingston 2GB USB pen drive

Table 2
Field experiment treatments

	No Rebate	$1 Rebate	$2 Rebate
Fast shipment	F0	F1	F2
Slow shipment	S0	S1	S2

identified as "experiment" sellers, we operated the two IDs on different days. Considering that there is a large number of sellers of the same object, our two IDs typically did not show on the same search page.

We created several treatments, with characteristics that vary along two dimensions. First, in different treatments we offered different levels of feedback rebate: 0, $1 and $2 per feedback. We clearly stated the rebate amount of $1 or $2 in the item listing title. Specifically, we used the title "Brand New Kingston 2GB USB Flash Drive" for a no rebate listing and "Brand New Kingston 2GB USB Flash Drive ($1 rebate available)" for $1 rebate listing (and the analogous title one for a $2 rebate). In the listings with a rebate, we added the sentence

> Rebate option. Your feedback is important to us; please give us your honest feedback and receive a $1 credit in your Paypal account.

The second dimension that distinguishes different treatments is transaction quality. Specifically, we provided the identical USB drives with different speeds of shipment. For a "fast" transaction, we shipped the USB drive immediately upon receiving payment. For a "slow" transaction, we shipped the USB drive two weeks after sale.

Together, rebate value (0,1,2) and shipment speed (F,S) create six different possibilities, as listed on Table 2. For example, treatment F1 corresponds to Fast shipping speed and a $1 rebate, while treatment S0 corresponds to Slow shipping and no rebate offered.

Our experiment may be chronologically divided into 4 phases, as listed on Table 3. In Phase 1, our RA mistakenly offered a $1 rebate right after receiving payment and *before* buyer feedback was received. Later we discuss how we treated this data. By the time we started Phase 2, both of our eBay IDs had 100+ positive feedback scores. In Phase 2 we offered the same feedback reward as in Phase 1, but we consistently made such rebate conditional on receiving buyer feedback. Thus Phase 2 corresponds to the F1 treatment (and F0 as well, for we only offered a feedback reward on some transactions).

In Phase 3, our two hitherto similar sellers took different paths. For seller ID1 we switched to an F2 treatment, that is, we increased the value of the rebate from $1 to $2.

12. In phase 4, our RA mistakenly put $1 instead of $2 for one transaction, so among the 16 $2 rebate transaction, one of them is actually $1 rebate transaction. In our data analysis, we treat it as a $1 rebate transaction.

Table 3
Field experiment chronology

Phase	Dates	Seller ID	Type	# obs.
Phase 1	2010/02/23 – 2010/05/08	1	F1*, F0	18, 12
		2	F1*, F0	15, 15
Phase 2	2010/06/10 – 2010/08/19	1	F1, F0	14, 16
		2	F1, F0	15, 15
Phase 3	2010/10/06 – 2011/01/11	1	F2, F0	15, 15
		2	S1, S0	15, 16
Phase 4	2011/04/06 – 2011/09/01	1	S2, S0	16,[12]4

Table 4
Descriptive statistics (Phase 1-4)

Variable	N	Mean	St dev	Min	Max
Rebate	201	0.687	0.719	0	2
Price	201	3.823	1.573	1.04	11
Bidder count	201	4.000	1.338	2	8
Bid count	201	5.841	2.227	2	14
Bidder score	201	350	700	0	6454
Bidder positive perc.	201	0.983	0.107	0	1
Seller score	201	112	22	75	151
Seller positive perc.	201	0.998	0.007	0.956	1
Feedback	201	0.682	0.555	-1	1
Feedback lag (days)[14]	155	13.355	9.575	0	54

For seller ID2 we switched to a 2-week shipment while keeping the $1 rebate. Finally, in Phase 3 seller ID1 switched from fast to slow shipment, while keeping the $2 rebate.[13]

Table 4 displays basic descriptive statistics of the data generated by the experiment's various phases. We should also mention that, of the 201 completed transactions, in only 3 instances did the same buyer repeat a purchase from the same seller (there are a total of 17 repeat buyer sales in our data set, but most correspond to the same buyer purchasing from different sellers).

4. Results

In this section, we present the results from our experiment. We group them into several subsections, roughly following the list of hypotheses outlined in Section 2. As a preliminary

13. Some buyers filed complaints with eBay regarding slow shipping by our seller ID2, so that it no longer met the minimal "detailed seller rating requirements" in the "Seller performance standards." As a result, ID2 was not operating during our Phase 4. Due to the difficulty of getting the 2GB USBs as mentioned in footnote 10, we only have 20 observations in phase 4.
14. For feedback-received transactions only.

subsection, we compare Phase 1 (where feedback rewards were mistakenly given before feedback comments were made) with the remaining phases. Then, we investigate whether offering a feedback rebate induces buyers to give feedback more frequently. Next we look at the nature of feedback, that is, whether it becomes more favorable to the seller (conditional on transaction quality). Following that, we look at the timing of feedback. Finally, we focus on the bidding stage, both in terms of bid level and number of bidders.

■ **Show me the money.** As mentioned earlier, a communications error led our RA to mistakenly offer a $1 rebate *before* receiving feedback during an initial stage of our experiment. We denoted this phase as Phase 1 and initially decided not to use it for our statistical tests (to the extent that we are interested in the effect of *conditional* feedback rebates). However, we decided this was a good opportunity to "turn lemons into lemonade:" our unintentional mistake provides a test of whether or not the conditionality of the feedback rebate (on actually receiving feedback) plays a role.

Both Phases 1 and 2 contain 60 fast-shipping transactions. In both cases we have 12 transactions with no feedback and the remaining 48 with positive feedback. In other words, in terms of frequency and type of feedback the two phases are identical: the conditionality of feedback seems to have no effect on incentives to give feedback. Moreover, restricting to the 48 transactions when feedback was given, we observe that the mean number of days before feedback is given is marginally lower when the rebate is given after feedback. Specifically, we use a one tail t-test and find $p = 0.0610$.

Together, these results suggest that incentives do not seem to play an important role, either because buyers are unaware of or incredulous about the seller's offer, or because reciprocity considerations play a bigger role than economic incentives. According to Bénabou and Tirole (2003),

> A central tenet of economics is that individuals respond to incentives. For psychologists and sociologists, in contrast, rewards and punishments are often counterproductive, because they undermine intrinsic motivation.

Our study suggests that the effects of conditional feedback go beyond those of economic incentives; in fact, they may consist primarily of motivational incentives. In fact, the analysis that follows largely confirms this suspicion, by providing ample support for the three HRs but very little for the three HE hypotheses.

Moreover, given the regularity of the effect of rewards on behavior, independently of whether they are given conditionally or unconditionally, in our regression analysis we aggregate data from all phases.

■ **A penny for your thoughts.** The first research question in which we are interested is whether paying for feedback induces buyers to give feedback more frequently. Table 5 tabulates the frequency of feedback for different types of feedback policy. We restrict ourselves to fast shipment transactions, so as to control for quality. In this table, we limit ourselves to transactions in Phase 2 by both sellers and Phase 3 by seller 1, a total of 90 observations. As can be seen, the percentage of transactions where feedback is given increases from 76.09% to 79.31% as we move from no rebate to a $1 conditional rebate, and from 79.31% to 93.33% as we switch from a $1 to $2 conditional rebate. In terms of statistical significance (t test), the mean value of propensity to leave feedback in $1 treatment is not

Table 5
Feedback behavior fast shipment transactions

Feedback reward →	None		$1		$2		Total	
Outcome ↓	#	%	#	%	#	%	#	%
No feedback given	11	24	6	21	1	7	18	20
Positive feedback given	35	76	23	79	14	93	72	80
Total	46	100	29	100	15	100	90	100

Table 6
Regression analysis of feedback behavior

Dependent variable[15]	Any feedback	Any feedback	Negative Feedback	Negative Feedback	Days till feedback	Days till feedback
Regression type	Logit	Logit	OLS	OLS	Tobit	Tobit
$1 rebate ($\beta_1$)	0.065 (0.067)	0.015 (0.076)	-0.046 (0.038)	-0.012 (0.041)	-0.481 (1.744)	-1.591 (1.951)
$2 rebate ($\beta_2$)	0.103 (0.123)	0.285 (0.183)	-0.121* (0.069)	-0.003 (0.081)	0.658 (3.204)	1.234 (3.855)
Slow shipping (β_3)	-0.341** (0.150)	-0.336** (0.150)	0.240** (0.095)	0.406*** (0.105)	-10.63** (4.111)	-12.54*** (4.608)
$1 rebate × Slow shipping (β_4)		0.173 (0.156)		-0.213** (0.095)		5.307 (4.293)
$2 rebate × Slow shipping (β_5)		-0.440 (0.288)		-0.394*** (0.143)		-1.278 (6.909)
Seller score (β_6)	-0.053*** (0.015)	-0.052*** (0.015)	-0.018* (0.010)	-0.019** (0.010)	-0.931** (0.417)	-0.923** (0.416)
Seller's perfect record (β_7)	0.078 (0.179)	-0.010 (0.185)	0.383*** (0.108)	0.403*** (0.108)	5.534 (4.894)	4.420 (5.025)
Date (β_8)	0.013*** (0.003)	0.013*** (0.004)	0.006** (0.003)	0.006** (0.003)	0.224** (0.113)	0.223** (0.113)
Seller and phase F.E.	Y	Y	Y	Y	Y	Y
N	201	201	155	155	201	201
Adj. R^2			0.256	0.302	0.0143	0.0156
Pseudo R^2	0.099	0.118				

significantly higher than in $0 treatment ($p = 0.3747$), whereas it is significantly higher in $2 rebate treatment than $0 rebate treatment ($p = 0.0747$). The results hold regardless of whether we we include phase 1's data into analysis or not.

In other words, our tabulation results suggest that feedback rewards induce higher feedback rates in fast shipping transactions, though weakly: when we offer $1 for customer feedback we don't observe a significant increase in the feedback rate; a $2 reward however leads to an increase in the feedback rate that is economically and statistically significant.

We next turn to regression analysis. Motivated by our results regarding unconditional rebates, we include Phase 1 in the dataset we use for multivariate regression analysis.

15. Note: Std. Err. in parentheses; * for $p < 0.1$, ** for $p < 0.05$, *** for $p < 0.01$. The data used in column (3) and (4) exclude no-feedback transactions, and the coefficients and standard errors reported in column (1) and (2) are marginal effects at the means.

However, we control for phase fixed effects to allow for the possibility that there is an effect we were unable to measure in our earlier data tabulation.

Column (1) and (2) of Table 6 show the results of a logit regression where the dependent variable is the dummy "any feedback was given in the transaction." In this regression, we pool all of our 201 observations.[16] Marginal effects, evaluated at the independent variable mean, are reported (delta-method standard errors are reported in parentheses). Of particular interest, the coefficients on feedback rebate (either \$1 or \$2) are positive but not statistically significant.

Together with the simple tabulations, the regression results provide fairly weak support for HE1, which predicts that feedback rewards lead to more feedback being given. We find that rebates do not make buyers more likely to leave feedback as we fail to reject the hypothesis that the coefficients associated with rebate are all equal to zero ($\beta_1 = \beta_4 = 0$ and $\beta_2 = \beta_5 = 0$).[17] The results suggest that the sign of the variation on rebate is consistent with HE1, but the coefficient is not statistically significant.

The regressions reported in Table 6 also show that slow shipping matters: we reject the hypothesis that the coefficients associated with slow shipping are all equal to zero ($\beta_3 = \beta_4 = \beta_5 = 0$).[18] For example, in column (2), the estimation of β_3 is -0.336, statistically significant at 5% level. This means that under the no rebate treatment, holding all other variables at the mean, the probability of leaving feedback is 33.6% lower in slow shipping cases than in fast shipping cases.

Finally, although our theory makes no specific prediction regarding the effect of sellers' record (or the dummy "seller's perfect score"), the results in Table 6 (columns (1) to (4)) suggest that a seller with a better score is less likely to receive some feedback and more likely to receive negative feedback. We find this result somewhat puzzling. One referee suggests that this may be related to buyer expectations: buyers hold higher expectations from sellers with a better record, and as a result are more likely to be disappointed and give negative feedback if they are not completely satisfied.

■ **Can buy me love.** The next question of interest is whether the *nature* of buyer feedback is altered by the fact that a reward is offered by the seller. In other words, we now inquire whether feedback rebates work as "bribes," whereby reciprocity-minded buyers feel compelled to provide better feedback (more positive, less negative) than their reward-free experience would lead them to. This corresponds to our hypothesis HR1.

Within the set of fast shipment transactions, our results are inconclusive because all feedback was positive. This limitation of our first treatments led us to consider a second set of treatments. We purposely shipped our USB drive more slowly (exactly 14 days after receiving payment) and repeated the shift from no feedback to \$1 and \$2 conditional feedback (treatments S1 and S2, respectively).

Table 7 displays the results from this new treatment. As before, higher feedback rewards increase feedback frequency (from 60% to about 75%). The novel test that Table 7 allows for is whether paying for feedback alters the *nature* of feedback. We observe that as we shift from no rebate to a \$1 or \$2 rebate the percentage of positive feedback within transactions with feedback increases: from 58 to 75 and to 91%, as the reward for feedback increases

16. Later we return to the issues of alternative samples to consider for regression analysis.
17. $p = 0.3695$ for the first test, $p = 0.2506$ for the second one.
18. $p = 0.0396$

Table 7
Feedback behavior in slow shipment transactions

Feedback reward →	None		$1		$2	
Outcome ↓	#	%	#	%	#	%
No feedback given	8	40	4	25	4	27
Some feedback given	12	60	12	75	11	73
Total	20	100	16	100	15	100
Positive	7	58	9	75	10	91
Negative	2	17	2	17	0	0
Neutral	3	25	1	8	1	9

form 0 to $1 to $2. In terms of statistical significance (t test), the mean value of propensity to leave feedback in $1 treatment is not significantly higher than in $0 treatment ($p = 0.3096$), whereas it is significantly higher in $2 rebate treatment than $0 rebate treatment ($p = 0.0770$).

Next, we return to regression analysis to address the question of the nature of feedback. In the second set of regressions (columns (3) and (4) in Table 6), we run a linear probability model on whether feedback is negative.[19]

This regression allows us to detect biases in the nature of feedback. From the results in column (4) of Table 6, we find that under fast shipping treatment, neither a $1 nor a $2 rebate have an effect on the probability of negative feedback (in comparison to the no rebate case); that is, neither β_1 nor β_2 are significantly different from zero. However, we find that, under slow shipping treatment, both a $1 and a $2 rebate have a significant effect on the probability of receiving negative feedback (both are significant at the 1% level).[20]

To see whether rebates matter overall, we run joint tests and reject the hypothesis that the coefficients associated with rebates are equal to 0.[21] To compare the difference between the effect of $1 and $2 rebate, we run joint test and cannot reject the hypothesis that the difference is zero.[22]

To get an idea of the size of the feedback rebate coefficients, we note that, that under the slow shipping treatment, the probability of leaving negative feedback is 22.5 percentage points lower when a $1 rebate is offered; and 39.7 percentage points when a $2 rebate is offered.[23] These results suggest that, consistently with HR1, the relative likelihood of negative feedback with respect to positive feedback is decreasing in rebate.

In sum, tabulation and regression results suggest that, even if you can buy feedback, you may not be able to buy unbiased feedback: reciprocity comes into play and what the

19. Following previous evidence that neutral feedback is commonly interpreted as negative, we pool neutral and negative feedback messages into one single category, which we call “negative.” See for example Cabral and Hortaçsu (2010). ”Negative feedback” in columns (3) and (4) is defined as a dummy variable that equals 1 if feedback is negative or neutral, and equals 0 if feedback is positive. Since fast shipping perfectly predicts non-negative feedback, many observations are dropped when we run a logit model. For this reason, we use linear probability model instead of logit model.
20. For the $1 rebate case: $\beta_1 + \beta_4 = 0$, $p = 0.010$; For the $2 rebate case: $\beta_2 + \beta_5 = 0$, $p = 0.001$.
21. For the $1 rebate case: $\beta_1 = \beta_4 = 0$, $p = 0.034$; for the $2 rebate case: $\beta_2 = \beta_5 = 0$, $p = 0.004$.
22. Under fast shipping treatment, $\beta_2 = \beta_1$, $p = 0.9253$; under slow shipping treatment, $\beta_2 + \beta_5 = \beta_1 + \beta_4$, $p = 0.2136$.
23. That is, $-0.213 - 0.012 = -0.225$ and $-0.394 - 0.003 = -0.397$.

seller ends up buying is positive feedback, not honest feedback.

As mentioned earlier, in one set of treatments we purposely lowered the value of q (by slowing down shipment). This allows us to test HR2, namely the hypothesis that the nature of feedback changes with q: a lower q leads to more negative and less positive feedback.

Table 7 provides a first piece of evidence consistent with HR2: whereas our fast-shipping transactions received exclusively positive feedback, our slow-shipping transactions received four negative feedback comments (the total number of negative and neutral feedback comments are nine). Using a t-test, we confirm that the negative feedback rate following a slow shipment transaction is statistically different from the negative feedback rate following a fast shipment transaction ($p = 0.0002$).[24,25]

The results from tabulation are confirmed by regression analysis. From the results in columns (3) and (4) of Table 6, we find that slow shipping has a significant effect on the probability of getting negative feedback with respect to positive feedback.[26] From the results in column (4), we find that under the no rebate treatment, the probability of getting negative feedback is 40.6% higher for slow shipping transactions than for fast shipping transactions. Under the \$1 treatment, the probability of getting negative feedback is 19.3% ($0.406 - 0.213 = 0.193$) higher for slow shipping transactions than for fast shipping transactions.[27] Under the \$2 rebate treatment, the probability of getting negative feedback is not significantly higher for slow shipping transactions than for fast shipping transactions.[28] These results provide support for HR2: the relative likelihood of negative feedback with respect to positive feedback is higher when transaction quality is lower (at least for non-\$2 rebate ones).

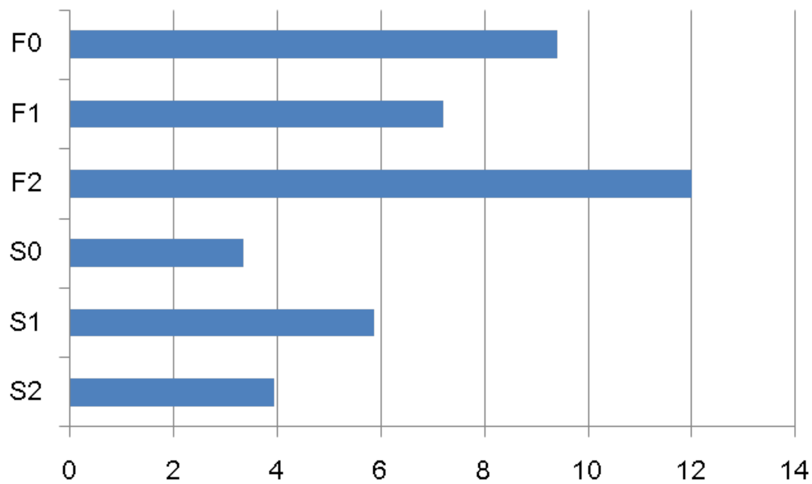
■ **The Avengers.** Do feedback payments change the timing of feedback? To the extent that buyers have positive time discount, we should expect that feedback rebates lead economically minded buyers to leave feedback quicker; this is the thrust of HE2. Figure 2 presents summary data that addresses this possibility. We create the variable "Days To Received Feedback" by computing the difference between "Date Feedback Left" and "Auction End Date." In the case of delayed auctions, we subtract an extra 14 days to account for the delay in shipping with respect to fast shipment transactions. In other words, we create the variable so as to measure the lag between the moment the buyer receives the good and the moment the buyer provides feedback. To summarize:

$$\text{DTRF} = \begin{cases} \text{DFL} - \text{AED} & \text{if prompt shipping} \\ \text{DFL} - \text{AED} - 14 & \text{if 14 day shipping} \end{cases}$$

where

24. The same is true if we consider both neutral and negative feedback as negative feedback ($p = 0.0000$.
25. As an aside, we note that the lack of negative feedback for Normal transactions should not be ascribed to "fear of retaliation," as several authors have previously argued. First, we (the seller) always give positive feedback promptly, so buyers have no reason to fear retaliation. Second, we do observe an increase in negative feedback as we reduce service quality.
26. For instance, from the results in column (4), the test of $\beta_3 = \beta_4 = \beta_5 = 0$ yields $p = 0.0006$.
27. For $\beta_3 + \beta_4 = 0$, $p = 0.073$.
28. For $\beta_3 + \beta_5 = 0$, $p = 0.935$.

Figure 2
Average number of days before feedback is received



DTRF: Days To Received Feedback
DFL: Date Feedback Left
AED: Auction End Date

We split the data according to our 6 treatments (three levels of feedback reward and two levels of transaction quality). Regarding the level of feedback, Figure 2 suggests a very weak effect. This prediction is confirmed by regression analysis. The regressions (columns (5) and (6)) in Table 6 show that the effect of feedback rebates on the speed of feedback is not statistically significant.[29] Overall, the empirical evidence provides little support for HE2.

A second prediction regarding speed of feedback relates to the change in transaction quality. As mentioned earlier, previous work has shown that there is such a thing as demand for justice (cf Section 2). In the present context, this would lead us to expect that delayed transactions create a greater demand for feedback (especially negative feedback), and that this would be given quicker. This is the thrust of our hypothesis HR3.

Figure 2 suggests that HR3 does indeed hold. In fact, the average number of days for leaving negative and neutral feedback is 4.7, while the average number of days for leaving positive feedback (in phases 2–4) is 11.2 days. When we include all phases, the average numbers of days are very similar: 4.7 and 10.5, respectively. These tabulation results are confirmed by regression analysis: column (5) in Table 6 shows that the coefficient on the dummy variable "slow shipping" is −10.63; in other words, on average slow transactions lead buyers to give feedback with a delay (with respect to shipping date) that is about ten days shorter than for fast shipment transactions.

■ **Free lunch.** Different bidders have different costs of providing feedback. As suggested by

29. We fail to reject the hypothesis that the coefficients associated with rebate are all equal to zero: for $\beta_1 = \beta_4 = 0$, $p = 0.448$; and for $\beta_2 = \beta_5 = 0$, $p = 0.950$.

Table 8
Feedback reward and bidding behavior

Rebate ($)	0	1	2
Average price	3.44	3.51	3.15
Bidder count	3.65	3.82	3.53
Bid count	5.26	5.53	4.97
N	66	45	30

the results above, even when no rebate is given, a considerable fraction of buyers do provide feedback. Therefore, when the seller pays for feedback to any buyer who is willing to do so, the marginal effect of such a payment is small in the sense that only a few buyers switch from not giving feedback to giving feedback. For this reason, it might seem that obtaining those marginal feedback comments comes at a very high cost (that is, a large amount of feedback rebates are given for a small number of extra feedback comments). However, an economically-minded, forward-looking buyer with zero feedback cost — one who would give feedback regardless of the rebate — should anticipate a gain of $1 or $2 (as the case may be) and this anticipated gain should be reflected in her bid. Even if the cost of giving feedback is not zero, to the extent that it is lower than the feedback reward, a rational buyer should expect a net gain from bidding in an auction with the promise of feedback reward. This is the thrust of HE3, the hypothesis that greater rebates for feedback should lead to higher bids (and a higher number of bidders).

Table 8 displays average price, bidder count, and number of bids for each treatment in Phases 2–4.[30] The data suggests that, contrary to the (economic) theory prediction, there is not much difference in bidding behavior resulting from rebate promises.

This is confirmed by regression analysis, the results of which are reported in Table 9. Differently from the previous set of regressions, we do not include phase fixed effects since buyers do not know they are in treatments F or S when they make purchase decisions. In particular, the fact that a rebate was (mistakenly) given before feedback was received (in Phase 1) should have no effect on bidding behavior. We do keep, however, seller fixed effects. The first regression looks at the determinants of sale price. Contrary to HE3 (and in accordance with the tabulation results) we see that feedback rebates have no significant effect on price. The regression coefficients have the right sign but are not statistically significant. We do observe, however, a significant negative coefficient on the variable seller score, similarly to the first set of equations. In this case, the sign of the coefficient is particularly striking as standard reputation theories would predict it to be positive. However, the coefficient

30. The results do not change if we include Phase 1's data as well.

size is very small, a mere 6 cents of the dollar, or roughly about 2% of sale price.[31] Finally, the coefficient of the variable "Seller perfect score," which theory would predict to have a positive sign, is not significantly different from zero (and has a negative sign).

A similar pattern is observed in the second and third regressions (number of bidders and number of bids), where the only statistically significant coefficient is that of seller score — and with a negative sign. Since the seller score steadily increases over time, one might think that this variable is measuring something other than the buyers' estimate of the seller's value. However, we include the calendar date in all regressions and this variable seems not to be significant. The negative effect of seller score on bids remains a puzzle to us (see also the discussion on page 11).

Overall, the results show that the rebate variables have no significant effect on bidding behavior. In sum, we find no evidence for HE3. We find this result important, among other things, because it shows that the cost of a feedback program, in terms of dollars per comment, may be considerably higher than what economic theory would predict.

In principle, there are several interpretations for the absence of an effect of feedback rewards on bidding behavior. One is that buyers are myopic, in the sense that at the time of bidding they do not take into account the future savings provided by the feedback rebate. An alternative explanation is that buyers are incredulous about the feedback rebate offers. Still another alternative explanation is that buyers are simply unaware of the feedback rebate promise.

■ **Robustness analysis.** We ran a series of additional regressions to test the robustness of our results. We repeated the regressions in Table 6 using data only from Phases 2-4, and the general results still hold. The results suggest nevertheless that slow shipping is an important determinant of negative feedback, which further confirms HR2. Next, we ran linear probability models for the dependent variable negative or non-negative feedback by considering (a) both positive and no-feedback as non-negative feedback, or (b) only no-feedback as non-negative feedback. We found that in both cases a $2 rebate continues to have a significant effect on lowering the probability of getting negative feedback under the slow shipping treatment, and that the effect of a $1 rebate is not significant. Further, we ran a linear probability model on the dependent variable leaving positive or non-positive feedback by considering (a) both negative and no-feedback as non-negative feedback; as well as (b) only no-feedback as non-positive feedback. We found that a $1 rebate still has a significant effect on increasing the probability of getting positive feedback under slow shipping treatment, and that a $2 rebate has no significant effect.

31. Over time the demand for 2GB USB decreased. Moreover, negative feedback began to be observed as slow shipping transactions took place. As a result, one would expect price and number of bidders to decline. We did a robustness check by only using data from phases 1 and 2 (during which the demand was about the same and no slow shipping transactions took place). We found that the coefficient of seller score is positive and significant at the 10% level in the OLS regression on price, not significant in the other two regressions. We repeated the test in phases 3 and 4 (when slow shipping transactions were introduced and the 2GB USBs were no longer produced by Kingston). For this subsample we not find any significant effect of seller scores. All in all, we believe the negative coefficient in the overall sample corresponds to bidders observing negative feedback in phases 3 and 4, which in turn affected their bidding behavior in a way that is picked up by the seller score variable.

Table 9
Regression analysis of bidding behavior (all OLS regressions)

Dependent variable	Price	Number of bidders	Number of bids
$1 rebate	0.050 (0.227)	-0.018 (0.199)	0.107 (0.335)
$2 rebate	0.029 (0.389)	-0.059 (0.34)	-0.617 (0.573)
Seller score	-0.062** (0.027)	-0.065*** (0.023)	-0.125*** (0.040)
Seller's perfect record	0.163 (0.570)	0.540 (0.498)	1.105 (0.839)
Date	0.006 (0.005)	0.009* (0.005)	0.019** (0.008)
Seller F.E.	Y	Y	Y
Constant	9.568 (1.895)	9.335 (1.655)	15.37 (2.791)
N	201	201	201
Adj. R^2	0.147	0.1	0.116

5. Discussion and concluding remarks

Table 1 summarizes the hypotheses we set out to test. They are based on two alternative paradigms of buyer behavior, one based on economic rationality (homo economicus), one based on psychological behavior (homo reciprocus). Overall, the evidence favors the latter paradigm. We find very weak and no evidence, respectively, for HE1 and HE2, the hypotheses that feedback rewards lead to more (HE1) and quicker (HE2) feedback. We also find no evidence for HE3, the hypothesis that feedback rewards affect bidding behavior (size of bids, number of bidders, or number of bids).

By contrast, we find fairly strong evidence in favor of the homo reciprocus paradigm. Specifically, we find that increasing feedback rewards changes the nature of feedback, with a greater share of positive feedback and a lower share of negative feedback being given (HR1); that lowering transaction quality (slower shipment) leads to a lower share of positive feedback and a greater share of negative feedback being given (HR2); and that lowering transaction quality speeds up the arrival of negative feedback (HR3).

All in all, our results suggest that it is possible to increase the feedback rate by means of giving conditional feedback rebates. However, this is a rather costly means of obtaining feedback. Moreover, it is likely that the nature of feedback will be considerably affected by rebates: you can buy feedback but you cannot buy unbiased feedback.

On March 2012, China's leading online trade platform (with 500 million registered users), Taobao, started a conditional feedback reward system. This development came to us as a surprise and was implemented well after we designed and ran our field experiment. Although it refers to a different trade platform (Taobao as opposed to eBay) and was designed in a slightly different way, the new Taobao scheme provides additional motivation and relevance for our work.

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