Some clues to the determinants of feedback behaviour

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ABSTRACT
We report the results of an experiment designed to investigate the determinants of feedback behaviour in electronic markets. Ratings driven by disconfirmed expectations should in principle reduce the asymmetric information problems of these markets. However, some other motives may influence the decisions of the sellers. In particular, empirical evidence suggests that the economic surplus obtained from the transaction may have some bearing on the way sellers are rated. Our design was meant to test whether and to what extent disconfirmed expectations and/or the transaction surplus play a role in determining the feedback behaviour of buyers in e-marketplaces. The results indicate that both factors affect the ratings, the latter having the stronger effect. One possible empirical implication could be that when an online purchase is a good deal a seller will typically get away with (moderately) exaggerated descriptions of the good on sale, obtaining a positive rating from the buyers.

Categories and Subject Descriptors
H.3.5 [**Online Information Services**]: Online Information Services - Web-based services

General Terms
Economics, Reliability, Experimentation.

Keywords
Reputation systems, feedback behaviour, electronic markets, electronic commerce.

1. INTRODUCTION
Electronic reputation mechanisms based on feedback are fundamental tools to mitigate risks involved in online transactions, which typically suffer from the consequences of information asymmetries more severely than standard markets. Such systems however are still far from perfect (see [6]). Most of the literature on feedback systems focuses on the effects of sellers' feedback on the probability of selling (see [11]) on the price premium obtained ([10]; [7]), or both ([3]; [12]). Feedback profiles could affect both prices and the probability of sale, but the evidence on the precise effects is mixed. While the literature has mainly examined the effects of online feedback, the present paper concentrates on its determinants. Previous research ([1], [8]) suggests the impact of disconfirmation (i.e. the difference

between expected and realized outcomes) on post-transaction customer satisfaction. A significant mismatch between the good actually delivered and what the customer expected results, through the lever of disconfirmation, in the negative rating of an untrustworthy seller. Should the agents conform to this behaviour, the asymmetric information problems in the market would be greatly reduced. However, can other factors be ruled out such as whether the transaction was a good deal? Empirical evidence provided by e.g. Jin and Kato [9] suggests otherwise: in online markets for collectibles, items whose quality is lower than advertised often get sold. Nonetheless most transactions end up with a positive feedback, particularly when the selling price is low with respect to the value of the goods.

We devised a laboratory experiment to expose the role of the transaction surplus as a possible determinant of feedback given by the buyers. Our results support the hypothesis that the transaction surplus, proxied within the experiment by the buyers' payoff, appears to be quite significant. A good deal in our experiment seems to strongly compensate for some disconfirmation, thus leading to biased feedback profiles [4].

2. EXPERIMENTAL DESIGN
The building blocks of the experiment are as follows. All subjects play the role of buyers and perform two tasks at each round. First, they have to buy a fictional item in a market, then they must leave a feedback about the seller, thus contributing to build a reputation system. Sellers are computer-generated; half of them are "good" (named "type A") and the other half are "bad" (named "type B") sellers, in a probabilistic sense explained precisely below. Subjects are enabled to distinguish type A from type B sellers once the transaction has been carried out. The initial profiles of the sellers are blank, so the feedback system emerges entirely endogenously from the experimental subjects' behaviour.

At the beginning of each of 30 rounds, every subject is randomly matched with three potential sellers, each offering an item whose value is advertised to be equal to 100 experimental points.[1] The experiment is built so as to guarantee that such advertised value can be considered a correct unconditional expectation for the value of the item (whereas conditioning on the type of seller, which is ex-ante unknown, returns different expectations). Each seller is characterized by information regarding its feedback profile and the price it proposes (which is randomly generated for each round and seller).

A buyer must choose from which one of the three sellers to buy. Then, the true value of the item bought is revealed and the type of seller can be unambiguously identified. In general the true value differs from the advertised value. Their difference, which

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[1] All relevant variables are denominated in experimental points, which are then converted to Euros according to a rate which is treatment specific.

we label as the "lie", is our experimental counterpart of disconfirmation. The payoff obtained in the transaction is equal to the difference between the true value of the item and the price paid. Finally, the buyer must rate the seller by leaving a feedback of the type "positive/negative" which is incorporated in the profile of the seller starting from the following round.

The experimental design is between-subjects and it involves two treatments whose defining factor consists in the signals that unequivocally identify the seller's type. Socially optimal behaviour calls for exploiting the signals to identify the sellers' type and rating them consistently leaving a positive feedback for types A and a negative feedback for types B.

In the *first treatment* type A sellers deliver items whose true value is a random integer drawn from the interval between 101 and 120 whilst type B sellers will deliver items whose true value is an integer between 80 and 100. Thus, the difference between true and advertised value of the item determines the type of seller. Because it is possible to earn little money from a type A seller, or much from a type B, the payoff may act as a confounding stimulus with respect to the socially optimal behaviour.

In the *second treatment* type A sellers deliver items whose true value is an integer between 21 and 40 points higher than the price paid, independent of the advertised value. Type B sellers deliver items whose true value is an integer between 0 and 20 points in excess of the price paid, again independently from the advertised value. Thus, the payoff from the transaction identifies the seller type. The "lie" is a confounding variable in this case. Indeed, the real value of the item may be either higher or lower than the advertised value independently from the type of the seller. Table 1 summarizes how the signals to identify the seller's type differ across the three different treatments.

Table 1. Seller's type signals in the two treatments

	Treatment 1	**Treatment 2**
Lie	Yes	No
Payoff	No	Yes

All sessions were conducted in May 2010 at the Behavioural and Experimental Economics Laboratory (BEELab) of the University of Florence, Italy. The 60 subjects (30 for each of the two treatments, 31 females and 29 males) were college students from various fields of study. The conversion rate between experimental points and Euros was 1.5 in Treatment 1 and 2 in Treatment 2 (to ensure equivalent incentives across treatments). Subject earned an average of €15.60. The experiment was programmed and conducted with the software z-Tree [5]. More details about the experiment can be found in [2].

3. RESULTS
3.1 Treatment effects
Table 2 displays the positive feedback rate resulting from the treatments for the two types of sellers.

Table 2. Final feedback profiles at a glance

	Treatment 1		**Treatment 2**	
	Type A	**Type B**	**Type A**	**Type B**
Positive ratings	83.0% (8.4%)	40.3% (8.9%)	93.4% (7.3%)	14.7% (9.4%)

Note: standard deviations in parenthesis

Remark that the observed behaviour significantly differs from the socially optimal benchmark: a considerable fraction of transactions end up with suboptimal rating choices, in the sense that the rating does not reflect the type of seller correctly particularly in Treatment 1. However, albeit imperfectly, the profiles do reflect the differences between the two types of sellers, so the reputation mechanism proved useful for the subjects. Different treatments resulted in different relative efficiency of the feedback system. In treatment 2 the feedback profiles endogenously created clearly identified the sellers' types. In the other two treatments the system performed worse. It is also of interest to study the patterns of "wrong" ratings (i.e. positive feedback left to type B sellers, and negative feedback left to types A) which are depicted in Figure 1 as fractions over total transactions for each round.
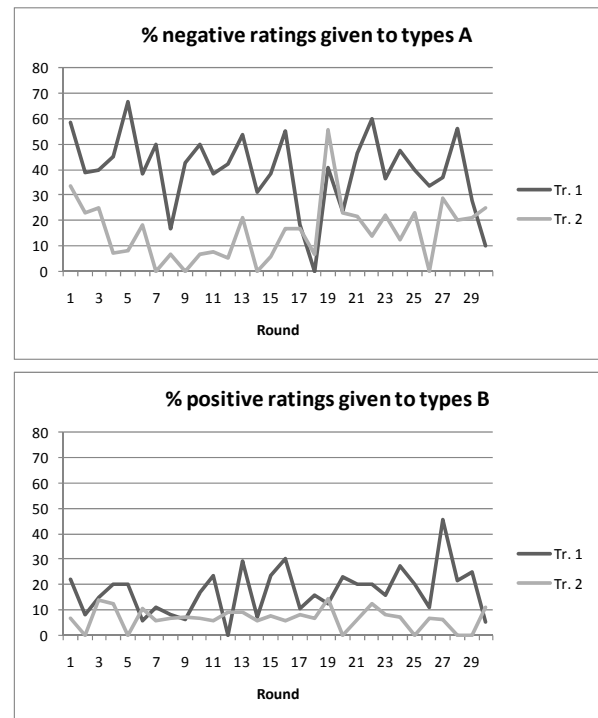

Figure 1. Fraction of "wrong" ratings per round

The fraction of wrong ratings is lowest for treatment 2, as already suggested by Table 2. The tests reveal that there are significant differences in the wrong feedback patterns across treatments both for types A and for types B.[2]

3.2 Regression analysis
In this subsection we present the results of our regression analysis on the determinants of feedback. Table 4 contains the logit estimations of a model of the determinants of positive feedback with the following explanatory variables: *lie* is the difference between the true value and the advertised value; *payoff* is the difference between the true value and the price; fb_{t-1} is the

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[2] The results of the Mann-Whitney tests are the following: 4.614 (*p-value* < 0.001), 5.118 (*p-value* < 0.001), for types A and types B respectively.

percentage of past positive feedback ratings over the total effectuated by the seller.

Table 3. Random effects logit models, determinants of feedback

	Treatment 1		Treatment 2	
	Coeff.	Change in probability	Coeff.	Change in probability
payoff	*0.070**** *(0.009)*	*0.220****	**0.230***** **(0.023)**	**0.620*****
lie	**-0.056***** **(0.012)**	**-0.142*****	*-0.017* *(0.011)*	*-0.067*
fb_{t-1}	0.001 (0.003)	0.008	0.014*** (0.004)	0.137***
Constant	-1.159*** (0.407)		-4.847*** (0.483)	
N	900		900	
LR χ^2	298.11 (df = 3)		738.06 (df = 3)	
Pseudo R^2	0.26		0.60	
% correct	75.44		89.00	

Note: *, **, *** significant at 10, 5 and 1% respectively; standard errors in parenthesis. Boldface indicates that the variable signals the type, italics encodes the confounding stimulus. The change in probability is the change in predicted probability of giving positive feedback for an increase of 1 standard deviation in each independent variable.

We ran estimations separately for each treatment (since in each of them the explanatory variable encoding the type of seller is different).[3] Both *lie* and *payoff* significantly contribute to the feedback behaviour in treatment 1, while the former has a non-significant effect in treatment 2. On the contrary, the seller's past cumulated feedback has a significant effect in the second treatment only, although quantitatively lower than that of *payoff*.

The relevance of the variable encoding the type of seller and of the confounding variables differs widely across treatments. In treatment 1 changes in *payoff*, which was confounding, had a larger impact on the probability of leaving a positive feedback than changes in *lie* (i.e surplus was more important than disconfirmation). In treatment 2, the situation is reversed: a one standard deviation rise in *payoff* increases the probability of giving a positive feedback by .62, versus an estimated -.07 for a similar change in *lie*. Finally notice that the models fit the observed behaviour of the subjects fairly well, especially in the second treatment where 89% of the cases are correctly predicted.

4. CONCLUSIONS

This paper studies the factors that trigger positive and negative ratings of sellers within an experimental trading environment with an endogenous reputation system based on feedback left by the buyers. In order to reduce asymmetric information about the sellers, buyers should punish buyers who lie about the real value of the goods they sell. However the leading factor driving the

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[3] We also estimated the model with fixed effects, with little gain with respect to the baseline model.

ratings is the economic payoff of the transaction. So, in our experiment a large enough payoff was typically conducive to rating a seller positively, even in the face of unambiguous evidence that the seller was a bad one. These results account for the propensity of some sellers on online marketplaces to overstate the qualities of the goods on sale. Real world examples include online markets for cards, stamps or other collectibles, in which many items' advertised quality is not quite up to their actual one (see [9]).

In terms of empirical implications, our findings support the inclusion of a measure of the quality price ratio obtained in the purchase within the detailed seller ratings available to buyers. This may be appropriate especially when the price is decided by the seller (rather than emerge as the outcome of an auction). This might help subsequent customers make sense of the usual bulk of nearly immaculate feedback profiles of the typical seller on e-marketplaces.

Various research questions remain to be addressed. In particular, it would be interesting to study the effects of losses on (experimental) feedback behaviour. Also, introducing an auction mechanism in the allocation of goods would considerably enrich the analysis. Indeed letting the buyer, to some degree, make the price and therefore affect the quality price ratio, may considerably modify buyers' rating behaviour.

5. ACKNOWLEDGMENTS

6. REFERENCES
[1] Anderson, E.W., M.W. Sullivan. 1993. The antecedents and consequences of customer satisfaction for firms. *Marketing Science* 12, 2 (Spring, 1993) 125-143. DOI=10.1287/mksc.12.2.125

[2] Colucci, D., Salotti, S., Valori, V. 2011. Good Bargains and Reputable Sellers: An Experimental Investigation of Electronic Feedback Systems. DiMaD Working Papers, 2011-04 (March 2011).

[3] Dellarocas, C. 2003. The Digitalization of Word of Mouth: Promise and Challenges of Online Feedback Mechanisms. *Management Science* 49, 10 (Oct. 2003) 1407-1424. DOI=10.1287/mnsc.49.10.1407.17308

[4] Dellarocas, C., C. Wood. 2008. The Sound of Silence in Online Feedback: Estimating Trading Risks in the Presence of Reporting Bias. *Management Science* 54, 3 (May 2008) 460-476. DOI=10.1287/mnsc.1070.0747

[5] Fischbacher, U. 2007. z-Tree: Zurich Toolbox for Ready-made Economic Experiments. *Experimental Economics* 10, 2 (June 2007) 171-178. DOI= 10.1007/s10683-006-9159-4

[6] Gavish, B., C.L. Tucci. 2008. Reducing internet auction fraud. *Communications of the ACM* 51, 5 (May 2008) 89-97. DOI= 10.1145/1342327.1342343

[7] Houser, D., J. Wooders. 2006. Reputation in Auctions: Theory, and Evidence from eBay. *Journal of Economics and Management Strategy* 15, 2 (Summer 2006) 353-369. DOI=10.1111/j.1530-9134.2006.00103.x

[8] Inman, J.J., J.S. Dyer, J.J. Jianmin. 1997. A generalized utility model of disappointment and regret effects on post-

choice valuation. *Marketing Science* 16(2), 97-111. DOI= 10.1287/mksc.16.2.97

[9] Jin, G.Z., A. Kato. 2006. Price, Quality, and Reputation: Evidence from an Online Field Experiment. *The RAND Journal of Economics* 37, 4 (December 2006) 983-1004. DOI= 10.1111/j.1756-2171.2006.tb00067.x

[10] Lucking-Reiley, D., D. Bryan, N. Prasad, D. Reeves. 2007. Pennies from eBay: The Determinants of Price in Online Auctions. *Journal of Industrial Economics* 55, 2 (June 2007) 223-233. DOI= 10.1111/j.1467-6451.2007.00309.x

[11] Yang, J., X. Hu, H. Zhang. 2007. Effects of a Reputation Feedback System on an Online Consumer-to-Consumer Auction Market. *Decision Support Systems* 44 93-105. DOI= 10.1016/j.dss.2007.03.005

[12] Zhang, J. 2006. The Roles of Players and Reputation: Evidence from eBay Online Auctions. *Decision Support Systems* 42 1800-1818. DOI=10.1016/j.dss.2006.03.008