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Negative Reputation Rate as the Signal of Risk in Online Consumer-to-Consumer Transactions

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ABSTRACT

Previous online reputation research has been focused on the effects of positive and negative reputations on trust formation, trading price, and probability of sale. We propose that negative feedback rate (NFR) is the most important indicator of the risk of buying from a seller online. This proposition has been supported by an empirical study based on data collected from eBay.com. We found that the 6-month NFR in the current period predicts much better the future risk measured by the NFR in the next 6-month period than did net reputation score and negative reputation score. A seller's life-long negative score in fact was not significant in predicting the future risk. In addition, a seller's age in the market was found to have similar predicting power on risk as did net reputation score.

Keywords: Reputation; Electronic commerce; Risk; C2C auction

1. INTRODUCTION

The prevailing online reputation systems, which provide trust-building mechanisms and assurance services on eBay, Yahoo auction, Amazon and many other online auction marketplaces, have contributed significantly to the success of the consumer-to-consumer (C2C) electronic commerce. The online reputation systems allow traders to leave each other a positive, negative or neutral rating after a transaction is finished. The scores are then added up as quantitative indicators of traders' reputation records which are available to future traders. In addition, traders can leave brief comments on their transactions or trading partners for further references.

The effectiveness of online reputation systems in the C2C auction market has triggered wide interests from the research community. According to the synthesis by Dellarocas [4], although some have investigated the effect on the probability of selling products [2], empirical studies on online reputation are unanimously focused on the effect of seller's feedbacks on item prices. However, because of the diverse nature of research design, such as different types and categories of items being investigated, different measures of reputation, different data collection processes, and different sample sizes, no consistent findings were found across these studies [13]. Positive feedback might or might not increase price or probability of sale, and the same applies to negative feedback and net reputation score, as Resnick et al. [13] summarize from 16 research reports. Whereas, accumulated positive and negative scores, as well as negative scores from a period of time, were found to be the most influencing

components of seller's reputation on buyer behavior.

On the other hand, some research has investigated the effect of risk or perceived risk on online trading and the adoption of trusted third party services (e.g., Antony et al. [1]; Hu et al. 2001 [7]). Perceived risk was identified as an important determinant of purchasing items and adopting trusted third parties' services in the electronic market. Further, perceived risk is subject to change with regard to each trading partner's online reputation.

The basic reputation indicators that can be obtained from a C2C online reputation system include positive score, negative score, and neutral score (less often used). Based on these three basic scores, three combination scores can be derived: the *total reputation score* which is the sum of positive, negative and neutral scores, the *net reputation score* which is the difference of positive score and negative score accumulated from the ratings from unique traders, and the *negative feedback rate* which is the ratio of negative score and the total reputation score. Presently, a majority of reported research uses positive, negative, and net reputation scores as the indicators of online reputation, but NFR has not been touched yet.

How do these reputation scores reflect the risk of trading with a seller? To our knowledge, little research has answered this question. So far, majority research effort is in the effect of reputation on trust, but not aimed at the measure of the risk in the C2C online transactions. The main research idea in this paper is described in Figure 1. In the dotted box of the figure is a typical model used in trust related research (see [8]),

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where perceived risk is investigated. However, the perceived risk does not necessarily match the real risk in the future, because online traders' behavior could be irrational. Therefore, this paper is intended to investigate the relationship between reputation indicators and the risk. We propose that a seller's negative feedback rate (NFR) is the most important indicator for predicting the risk of buying from him. Based on data collected from eBay, we conducted an empirical study. The result supported our proposition.

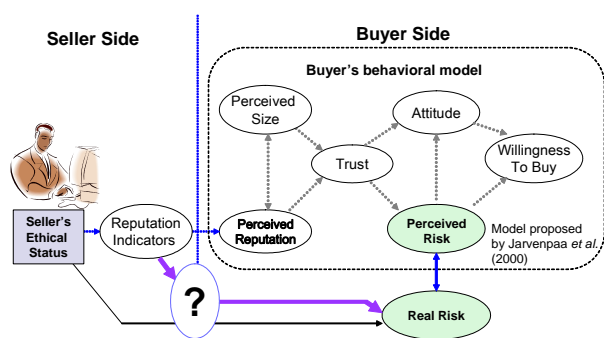


Figure 1: A conceptual model of the research

2. THEORETICAL BACKGROUND

2.1 Reputation

In the traditional reputation literature, reputation is generally defined as the consistency of an entity's behavior over a certain period of time [3][5][14]. It is a record of the history of an entity's interactions with others. Thus, reputation building is not a one-time effort but is based on the sum of all the past behaviors of the entity.

Reputation can be positive or negative. A positive reputation manifests all the favorable assessment of an entity, while a negative reputation shows the unfavorable aspects of the entity. Because the potential sacrifice associated with a negative or bad reputation is very high, an entity with a positive reputation is predicted to behave consistently in a favorable manner in the future. In buyer-seller relationships, the seller's reputation has a positive effect on buyer's trust in the seller and buyer's long-term orientation with the seller [6].

In electronic commerce research, Internet buyers are found to favor web sites that sell familiar products manufactured by familiar merchants [12]. The reputation of an online store is positively associated with an online consumer's trust in the store [8]. Further, research has shown that the negative reputation has much more effect than the positive reputation on buyers' trust because the negative reputation is the repeatedly appearance of a seller's unfavorable behavior that is highly associated with the potential trading risk in the future (See the review from Dellarocas [4] and Resnick et al. [13]).

2.2 Risk

According to classical decision theory, risk is "the variance of the probability distribution of possible gains and losses associated with a particular alternative" ([11], pp.1404). The definition is too abstract for the traders in the C2C auction market to understand. Following MacCrimmon and Wehrung [10], risk is defined as the chance or probability of loss. We thus define the potential risk of trading with a seller to be the probability of leaving the seller a negative feedback. Although the reputation system provides detailed comments about the negative reputation, a potential buyer may not have the resources (cognitive, motivational, or other external resources) to search the entire archive and find out the exact reasons for the negative comments. Further, risk is also associated with the significance of loss [11], e.g., how much a buyer can lose because of fraud.

2.3 The rationale of the research

In this research we focus on how online negative reputation can indicate the real risk in a future online transaction. This issue is represented by the question mark in Figure 1. Normally, a reputation system does not provide a direct causal link between the historical negative feedbacks and the information about the auctioned item, so that a buyer could not easily figure out the probability of future loss. Hence, we argue that a potential buyer will rely on the summarized reputation information in a seller's profile to judge the risk level of trading with the seller. The definition we have provided implies that risk is in the form of probability rather than a quantitative number representing the value of the loss. In the C2C online auction context, previous research has used negative feedback scores to measure risk. This measure is not accurate, because a negative feedback score does not reflect the probability of getting negative feedback in the future. The right measure of such risk should be a number signaling the probability of unpleasant consequences from the transaction with the involved seller. Thus, both the number of negative feedbacks the seller has received in a period of time and the total number of transactions in the same period of time should be considered together. We realize that there are several different types of NFRs, e.g., lifetime NFR and NFRs during different time periods. They are applicable to the same risk analysis purpose depending on different timeframes and accuracies. In the later discussion, we refer NFR as the NFR calculated from reputation scores in a 6-month period from now on.

3. AN EMPIRICAL STUDY

In this section, we report an empirical study based on data collected from eBay.com. The purpose of the empirical study is twofold. First, we aim to reveal the nature of the negative feedbacks through a content analysis of the feedback comments. We have not seen

any effort of analyzing the diverse contents of the reputation feedbacks. Second, we want to justify the predictive power of different reputation scores on the risk in the transactions with unknown sellers through a longitudinal study, using reputation score data collected at two time points.

3.1 Study 1 - Content Analysis of Negative Feedback Comments

For the content analysis, we randomly collected 216 unique sellers with negative reputation scores. We searched these 216 seller's transactional history archived on eBay.com. We randomly selected one piece of feedback comment associated with a negative rating to the seller.

As each online negative feedback may link to different stories and signal different types of perceived risks, such as financial losses, undesired low quality, and unsatisfied service, it is necessary to look into negative complaints in order to reveal their nature. We are interested in why buyers are unhappy with sellers and how buyers attribute those complaints.

The authors of this paper worked as independent coders of the feedback comments. After finishing coding two coders compared the results and resolved the differences and discrepancies with a detailed discussion. The reliability of inter-coders was 0.90.

The coding was focused on three basic questions: What are the causes of negative feedback, merchandize or service? Who are responsible for the negative feedback, the seller, the buyer, or the third party? Is the negative feedback resolvable?

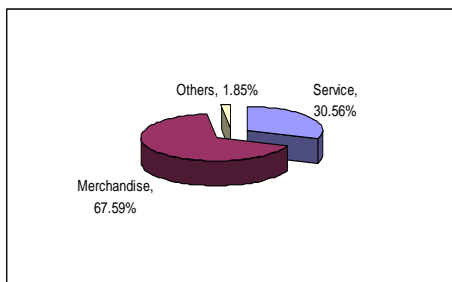


Figure 2: Causes of complaints

Results and Implications

The results of the coding on the three questions are shown in Figure 2-4 and Table 1. The three findings are discussed as follows:

Not every complaint is related to a merchandize problem

Figure 2 indicates that about two thirds of negative comments are complaints against merchandise problems. More than 30% complaints are related to seller services,

such as “shipped to wrong address”, “item received more than a month”, or “never response to my email”. Apparently these complaints are not related to any fraud, but reflect buyers' unpleasant experience. Thus, this type of risk is about unsatisfactory transaction that every buyer wants to avoid.

According to the responses from the seller, the buyer could be the number one trouble maker followed by the seller and the third party.

There are many attribution errors in the negative feedbacks left by the buyer. According to Table 1, more than one third of complaints are because of the buyer. Typically, an inexperienced buyer may not understand the information of the auctioned item well and does not follow the way as an experienced buyer does. This is particularly remarkable in the complaints about the merchandize. Although this is not the kind of the risk in the traditional sense, the over reaction of a buyer may incur the retaliation of the annoyed seller returning with a negative rating. So the backfiring from the seller or uncomfortable feeling of the regrettable outcome is the risk the buyer may face under this situation.

Table 1. The liable agents to the complaints

Complained issues	Seller	Buyer	3rd party	Others
Merchandise	18.49%	38.36%	15.07%	28.08%
Service	12.12%	28.79%	19.70%	39.39%
Overall	16.20%	36.11%	16.20%	31.49%

In addition, about one sixth of the complaints are related to the third party who provides delivery services, contracted packing services, or original product supply (Figure 3). Although this also has nothing to do with fraud, it is one kind of risks that a buyer may encounter. As shown in Table 1, sellers are responsible for less than half of the complaints as buyers are.

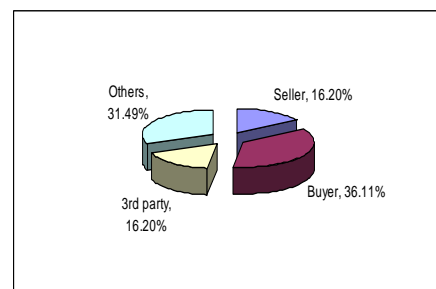


Figure 3: The composition of liable agents

More than 40% of the complaints are resolvable or have been resolved at the moment they are made.

Figure 4 shows that more than half of the complaints can be classified as disputes. Sellers are responsible for almost half of complaints (47.95%) to merchandises. Less than one fifth (18.49%) of the complaints against the merchandize has caused sellers' harsh responses and

ended unpleasantly. Practically, when a seller has responded to a buyer's complaint regarding the merchandise and a dispute is incurred, it becomes difficult to justify whether the case is a fraud or not. From a prospective buyer's angle, this is an undesirable situation and must be avoided.

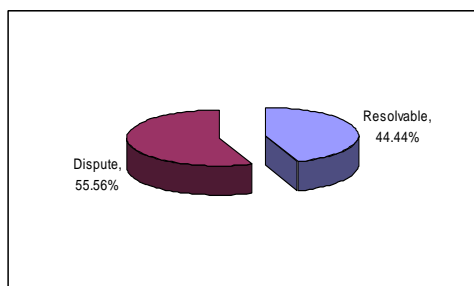


Figure 4: The resolvability of negative comments

3.2 Study 2 - Predictors of NFR

For the longitudinal analysis, we followed the data collection procedure reported in Lin et al. [9]. We first

collected 2,000 seller's reputation data in March 2003. Six months later, we repeated the data collection using the same 2,000 seller IDs. 174 sellers IDs were no longer active in the second round collection because these sellers have quitted the account, leaving 1,826 useful observations in the study.

Results

We tested how well the reputation indicators observed in the current 6-month period (t_0), i.e., NFR, net reputation score, accumulated negative feedback, and age, can predict an individual seller's NFR in the next 6-month period (t_1). We used stepwise regression to examine the correlation of the NFR in the next period to different reputation indicators. The results from the Tobit regression model and the OLS model are summarized in Table 2. Tobit regression model was used because the dependent variable NFR at the second point (t_1) was censored with a lot of 0's. In general, the regression results from the two models are consistent.

Table 2: Regression analysis of predictors of NFR in the next 6-month period
Dependent: NFR(t_1)

Tobit Model	Ln(NFR(t_0))	Age	Ln(Net(t_0))	Ln(Neg(t_0))	N	Log Likelihood
Model 1	0.87				1826	-640.40
Model 2		-0.0009			1826	-1281.76
Model 3			-0.40		1826	-1205.80
Model 4				-0.01ns	1826	-1031.06
Model 5	0.82	-0.0004			1826	-627.03
Model 6	0.78		-0.15		1826	-627.55
Model 7	0.89			-0.11 ns	1826	-633.27
Model 8	0.78	-0.0003	-0.10		1826	-622.96
Model 9	0.84	-0.0004		-0.06 ns	1826	-625.38
Model 10	0.69	-0.0003	-0.22	0.12 ns	1826	-621.50
OLS	Ln(NFR(t_0))	Age	Ln(Net(t_0))	Ln(Neg(t_0))	N	R ²
Model 1	0.87				468	0.5854
Model 2		-0.001			468	0.1252
Model 3			-0.44		468	0.2408
Model 4				0.01 ns	468	0.0002
Model 5	0.82	-0.0004			468	0.6084
Model 6	0.78		-0.15		468	0.6076
Model 7	0.89			-0.11 ns	468	0.5979
Model 8	0.78	-0.0003	-0.10		468	0.6152
Model 9	0.84	-0.0004		-0.06 ns	468	0.6112
Model 10	0.69	-0.0003	-0.22	0.12 ns	468	0.6176

ns: non-significant; All the other coefficients are significant at the 0.001 level

Implications

Seller's current NFR is the most significant variable for predicting the NFR in the next period

The most important predictor of future risk is the NFR in the current 6-month period, which explains the highest percentage of the variance of the next period

NFR (R^2 is about 59% from the OLS regression) among the four independent variables. This means that the NFR is the best among all four variable in predicting the risk of trading with an unknown seller in the C2C online auction market. The positive relationship suggests that the higher the NFR from the current period, the higher the NFR in the next period. The contribution of the other three variables in explaining the risk level is

marginal because their presence has little effect on the goodness of fit (for example, 63% vs. 59% of R^2 in the OLS regression, or -640 vs. -627 of logarithmic likelihood in the Tobit regression).

Net reputation score is negatively correlated to seller's NFR in the next period

The relationship between net reputation score and NFR is significantly negative, suggesting that the higher the net reputation score, the lower the NFR in the next period. This finding is consistent with the findings reported in previous literature, in which net reputation score has a significant effect on trust and price premium. Therefore, our study suggests that net reputation is also a significant predictor for the trading risk with a specific seller. However, the explanatory power of net reputation score (R^2 is about 24% in the OLS regression) is not as strong as NFR.

An explanation to the discrepancy of the effect of net reputation score is that when the net reputation score is high, the variance of NFR is low, because sellers with high net reputation scores tend to have high transaction volumes and their NFRs are relatively stable. The sellers with low net reputation score typically have lower transaction volume, and the variance of their NFRs is higher. Therefore, the NFR is more sensitive to the range of net reputation scores.

Seller's age matters in predicting NFR

The age of a seller also provides the similar explanatory power in predicting NFR (R^2 is about 13% in the OLS regression) as the net reputation score. This implies that the longer a seller stays on the market, the lower the NFR. Therefore, like net reputation score, a seller's age can be another important measure of his experience and tenure in the market. According to Lin et al. [9], in the context of market structure research, online reputation as the tangible asset for online traders reflect their capacity as virtual firms in the electronic market. Based on this, our study is the first one that has found that age is an effective measure of a seller's capacity in doing business on the market.

A seller's total negative score accumulated in his business life cycle has no effect on NFR

Unlike previous studies who have found significant effects of negative feedback on person's trust and price, this study did not find significant effect of negative reputation score on the next period NFR ($p > 0.05$). This suggests that without considering the total number of transactions from which the negative reputation score are generated, the risk in a trading cannot be predicted accurately. Negative reputation score, an absolute number rather than a relative number, cannot tell exactly whether it is likely to have an unpleasant outcome in the transaction with a seller. The previously reported significance of negative reputation score on traders'

behavior was only the implication of their irrationality.

According to the above findings, the maturity of a seller, signaled by his age and net reputation score, is important for estimating the risk level in transacting with him. We can refer to this as the "learning effect." The learning effect was also found from the negative relationship between transaction volume and negative rate ($\beta = -0.0002$, $p < 0.001$ $R^2 = 0.10$). The higher the number of transactions, the lower the NFR. Although an individual may maximize his effort to conduct a good business, his behavior is relatively consistent. If he has got higher NFR in the past, he is more likely to get higher NFR in the future. This implies that even though a trader changes his ID or identities on eBay, if he has got a high NFR, he is still likely to get the same level of NFR under a new ID, because his ability of doing business behind the pseudonym is unimproved. At the same time, the costs of switching ID and building new reputation may be high, which suggests to the sellers: *Do not change your ID when you have a high NFR. It does not work.*

4. CONCLUSIONS

In this paper, we analyzed the negative feedbacks by coding the textual complaint data and examined the determinants of future NFR with the historical reputation scores. We made two clear contributions to the research on C2C auction market. First, we revealed the diverse nature of negative reputation. Several important findings were derived from analyzing the content of the negative feedback comments. Second, we proposed to use NFR to measure the potential risk in trading with an unknown seller in the electronic market. The results of the empirical study could provide guidelines for the future buyers to do business online. The findings also have important implications for the design of reputation systems. Online companies are encouraged to report NFR as a measure of reputation of traders. We have noticed that since 2004 eBay.com has started to provide positive feedback rate on its online reputation forum (see Appendix). We reason that the positive feedback rate (PFR) might work as an incentive for sellers to maintain their reputation and promote the effectiveness of eBays' feedback forum. However, PFR is not as straightforward as NFR as an indicator of the risk, although rational buyers can derive NFR from PFR. If eBay.com can further show the positive feedback rate during a period of one month and 6-month, the figures will be more informative and valuable.

REFERENCES

- [1] Antony, S., Z. Lin, and B. Xu, "Determinants of Online Escrow Service Adoption: An Experimental Study," *The Proceedings of the 11th Workshop on Information Technology and Systems (WITS'01)*, 2001, pp71-76.

[2] Ba, S., and P. A. Pavlou, "Evidence of the Effect of Trust Building Technology in Electronic Markets: Price Premiums and Buyer Behavior," *MIS Quarterly* 26(3), 2002, pp243-268.

[3] Balachander, S., "Warranty Signaling and Reputation," *Management Science* 47(9), September 2001, pp1282-1289.

[4] Dellarocas, C., "Digitization of Word-of-Mouth: Promise and Challenges of Online Feedback Mechanisms," *Management Science* 49(10), 2003, pp1407-1424.

[5] Fombrun, C., and Shanley, M. "What's in a name? Reputation Building and Corporate Strategy," *Academy of Management Journal* 33(2), June 1990, pp233-258.

[6] Ganesan, S. "Determinants of Long-Term Orientation in Buyer-Seller Relationships," *Journal of Marketing* (58:2), April 1994, pp1-19.

[7] Hu, X., Z. Lin, A. B. Whinston., and H. Zhang, "Perceived Risk and Escrow Adoption: An Economic Analysis in Online Consumer-to-consumer Auction Markets," *The Proceedings of ICIS 2001*, 2001, pp271-274.

[8] Jarvenpaa, S. L., N. Tractinsky, and M. Vitale, "Consumer Trust in an Internet Store," *Information Technology and Management* 1(1-2), 2000, pp 45-71.

[9] Lin, Z., D. Li, B. Janamanchi, and W. Huang, "Reputation Distribution and Consumer-to-Consumer Online Auction Market Structure," *Decision Support Systems*, 2004, forthcoming.

[10] MacCrimmon, K, R. and D. A. Wehrung, *Taking Risks:The Management of Uncertainty*, Free Press, New York, 1986.

[11] March, J.G., and Z. Shapira, "Managerial Perspectives on risk and risk taking," *Management Science* 33, 1987, pp1401-1418.

[12] Quelch, J. A., and L. R. Klein, "The Internet and International Marketing," *Sloan Management Review* 37(3), 1996, pp60-75.

[13] Resnick, P., R. Zeckhauser, J. Swanson, and K. Lockwood, "The Value of Reputation on eBay: A Controlled Experiment," Working paper, 2004.

[14] Tadelis, S., "What's in a Name? Reputation as a Tradable Asset," *The American Economic Review* (89:3), June 1999, pp548-563.

APPENDIX:

A1: EBay's reputation forum before 2004

Feedback Summary

899 positives. 808 are from unique users.

3 neutrals.

1 negatives. 1 are from unique users.

[See all feedback reviews](#) for PQRtraders.

Member since: Wednesday, Jul 05, 2000 Location: United States

	Past 7 days	Past month	Past 6 mo.
Positive	7	30	88
Neutral	1	1	1
Negative	0	0	0
Total	8	31	89
Bid Retractions	0	0	0

A2: EBay's reputation forum since 2004

[Home](#) > [Services](#) > [Feedback Forum](#) > [Member Profile](#)

[Why does this page look different?](#)

Member Profile: XYZ_Traders (6008) Power Seller

Feedback Score:	6008	Recent Ratings:	
Positive Feedback:	99.2%		
Members who left a positive:	6055		
Members who left a negative:	47		
All positive feedback received:	7706		

	Past Month	Past 6 Months	Past 12 Months
positive	121	917	1662
neutral	1	4	10
negative	2	5	5

Bid Retractions (Past 6 months): 0

Member since: Oct-18-97
Location: United States

- [ID History](#)
- [Items for Sale](#)
- Learn more [About Me](#)

Contact Member