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RESEARCH ARTICLE

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Reputation in China's online auction market: Evidence from Taobao.com

Abstract Using data on prepaid cards for an online game listed on Taobao.com, this paper examines the impact of sellers' reputation on their sales in China's online market. It is found that sellers' good reputation has a positive impact on their sales volume, but the marginal effect of this impact decreases severely. We also find that sellers' affiliation with seller coalitions can increase their sales in a given period. Results show that individual and collective reputation can function well in the absence of mature law and social credit system related to online trade, and that private order can substitute public order in a market with immature laws as in China.

Keywords online auction, feedback system, reputation

摘要 借助淘宝网上的在线游戏预付卡等数据，研究中国网上销售中卖方信誉的作用，发现卖方的声誉对其销售量有正面的影响，但这种影响是非线性的。属于商盟的卖家在给定时间内的销售量高于不属于任何商盟的卖家，从而验证了在有关法律不健全和社会信用不完善的前提下，网上交易中卖家个人声誉和卖家所属商盟集体声誉在销售中的作用。

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关键词 网上交易，信用评价系统，声誉

1 Introduction

The past few years have witnessed an unusual boom in China's online auction market. According to the *17th and 18th Statistical Survey Reports on the Internet Development in China* published by China Internet Network Information Center(CINIC), in 2005, 37.9 million people in China had online shopping experience, a 152% increase than in 2004. The total of C2C transaction volume reached 13.7 billion yuan, about 1.7 billion US dollar—235% more than the level of 2004. Among others, EachNet and Taobao are the two leading domestic players in China's online auction market. EachNet is China's first auction website (and also the biggest one until 2004). In March, 2003, eBay purchased EachNet. Therefore, EachNet became eBay's 100% owned Chinese subsidiary. Taobao was founded by Alibaba, China's biggest B2B website. In September, 2005, Yahoo! bought a 40% stake of Taobao.

Taobao competes with EachNet by the same localization strategy. Taobao's online user community is much more active than EachNet's, which helps buyers and sellers exchange shopping information and increase user stickiness. Taobao also has an effective instant messenger that provides communications between buyers and sellers, while eBay users just begin to adopt Skype. The main difference between Taobao and EachNet is that Taobao is free of charge while EachNet charges sellers for listing and marketing items. In 2005, Taobao exceeded EachNet in the number of users and transaction volume. According to CINIC's annual survey report, the market shares of Taobao and EachNet were 57% and 34% respectively in 2005.

Although online shopping has lower information collection and dissemination cost, and the buyers and sellers can be matched more easily, it has certain inherent defects. The biggest problem with online auction may be moral hazards of the users. If sellers deliver goods to buyers first, sellers would risk default. If buyers pay deals first, they would worry that sellers may not deliver goods. This two-sided prisoner's dilemma impedes the development of online shopping. Auction website and other third intermediaries have established feedback system, escrow, online dispute resolution and other supporting mechanism to solve the problem. On eBay and Taobao, the frequency of auction fraud, non-delivery, and credit/debit card fraud and other fraud is very low, which indicates that feedback system and other mechanisms function well.

Every eBay and Taobao member has a profile in the feedback system. The profile has basic information about the member and a list of feedbacks left by their transaction partners from previous transactions, which form a public record of the user's performance in prior transactions. A potential bidder can learn more of a seller's history before he/she decides whether to buy the seller's goods. Hence, feedback profiles become a means by which honest sellers can eventually be distinguished from dishonest ones and some indexes of profile can represent traders' reputation.

However, in a community with numerous members like eBay and Taobao, how can reputation mechanisms function well? Since the transaction between a particular pair of buyer and seller is infrequent,[1] bilateral relational contract is not effective and cooperative behavior cannot be achieved. Folk theorem in standard repeated games can not explain the role of reputation mechanism played in communities with many members. Game theory simplifies this infrequent transaction as random matching game. Kandori (1992), Ellision (1994), and Okuno-Fujiwara and Postlewaite (1995) extended folk theorem of standard repeated game into random matching game. Their studies showed that even if information about the behavior of the sellers is not widely shared in the community, cooperative outcomes can be sustained and also robust.

In online auction market, eBay, EachNet and Taobao function as information intermediaries and provide information for their members. Feedback system makes information collecting and disseminating nearly costless, so reputation mechanism can play its role and thus solve the prisoner's dilemma in online shopping (Baron, 2002; Dellarocas, 2003).

This issue of whether a seller's reputation matters in determining the price that buyers are willing to pay for the seller's product has received much attention in literature on industrial organization theory. Theoretical models have typically generated a positive relationship between the reputation of the seller and the price (Klein and Leffler, 1981; Shapiro, 1983; Houser and Wooders, 2000). However, empirical analysis of this issue has been proved to be quite difficult, largely due to the difficulties in quantifying and measuring a seller's "reputation". The development of electronic commerce in recent years has created an environment in which this issue can be tested empirically, and there have been several studies that used online-generated data to study the effect of the seller's reputation on the buyer's willingness to pay. Their conclusions showed that sellers' good reputation measured by some indexes in member profile has a positive impact on auction price.

On American eBay, most sellers use English auction to sell their goods, while in China almost all sellers and buyers are used to fixed price auction (eBay Express offers a platform for buyers to buy items by the way of fixed price). Because transaction is more active in Taobao than in EachNet and Taobao

[1] According to a survey of Resnick & Zeckhauser (2002), 89.0% of all seller-buyer pairs conducted just one transaction during the time period, and 98.9% conducted no more than four.

introduced some transaction mechanisms, such as coalition system, which are accordant with China's practical situations, we hence choose Taobao to test the effect of seller's reputation on sellers' transaction in China's C2C market. We collect the data of virtual online prepaid game card auctions from Taobao manually. Compared to goods chosen by the papers above, online prepaid game cards are more homogeneous in nature. The empirical results show that sellers' individual reputation and sellers' affiliation with seller coalitions have positive impacts on their sales. We also make a reasonable conjecture about buyers' browsing and purchasing habit on Taobao: Some buyers establish a long-term relationship with some good-reputation sellers. That is to say, in addition to random matching trade, repeated trade also exists on the Taobao website.

The remainder of this paper is organized as follows. Section 2 describes the institutional details of Taobao. Section 3 introduces the process of data collecting and provides description of variables. Section 4 presents empirical results and section 5 concludes.

2 Institutional details of Taobao auctions

China's online auction market has some characteristics different from eBay due to the absence of related law and social credit system. While eBay defines its role as a third intermediary and provides merely an online marketplace and other important accessory services, China's auction websites need to further intervene in transactions. For example, Taobao has to provide online dispute resolution service, online payment instrument and other services. Seller coalition is also an institutional innovation suitable for China's circumstances initiated by Taobao. In this section, we will introduce some institutional details about feedback system and seller coalition in China's online auction websites, particularly in Taobao.

2.1 Feedback system

Feedback system is essential to online C2C auction. It was initiated by eBay and was soon imitated by Taobao and other auction websites. In a feedback system, sellers and buyers are required to rate each other after an auction ends. Hence feedback system provides a platform for collecting and disseminating information.

Like eBay, every Taobao member has a profile in the feedback system. The profile has basic information about the member and a list of feedbacks left by their transaction partners from previous transactions. Each feedback left consists of a positive, negative, or neutral rating, and a short comment. Feedback ratings are used to determine each member's feedback score. A positive rating adds 1 point to the score, a negative rating decreases it by 1 point, and a neutral rating has no impact.

The profile forms a public record of the user's performance in prior transactions. A potential bidder on an item, for example, can view all the comments left for the seller by other users. He can learn whether the seller has consistently delivered the item to the winning bidder, and whether he accurately describes the item for sale. Hence, feedback profiles become a means by which honest sellers can eventually be distinguished from dishonest ones. Therefore, some indexes of profile, such as feedback score, the ratio of positive ratings to all ratings and the ratio of negative ratings to all ratings can be used to measure sellers and buyers' reputation. Profile is equivalent to the history of play in game theory; however, feedback system can replace the history of play with very simple summary profiles without loss of efficiency (Dellarocas, 2003).

Different from eBay, Taobao separates members' feedback scores that they acquire as sellers from scores that they acquire as buyers. In this way, Taobao avoids some sellers acquiring high feedback score by buying items with small value, which makes feedback system measure seller's reputation more accurately.

Because leaving a feedback may cost traders, especially buyers, sometimes, buyers may not leave a feedback. However, feedback is public goods for the whole community. Therefore, sellers and buyers are required compulsorily to rate each other by leaving feedback at the end of each transaction according to rules in Taobao.

2.2 Seller coalition

Seller coalition is an institutional innovation initiated by Taobao. Taobao encourages sellers to establish organized coalitions. Sellers' self-management can reduce Taobao's cost. There are two types of coalitions in Taobao, industry coalition and city coalition. Seller coalition, especially city coalition can generate external effect, which benefits everybody in the coalition. Seller coalition can increase small sellers' bargaining power, reduce delivery cost and procurement cost. Small sellers can learn from each other and acquire additional business information.

Moreover, Seller coalition can use its collective reputation as a hostage to undertake credible commitment to buyers. If buyers are cheated by any member of a coalition, they can punish the whole coalition by no longer buying goods from any members of the coalition. Therefore, the cheat of any member of a coalition damages the collective reputation of the whole coalition. To prevent members' reneging or fraud, initiators or organizers must check applicants' identities strictly. Only sellers' with high reputation can join coalitions. After sellers join coalition, their behaviors are monitored by other coalition members. If coalition members cheat, initiators will dispel them. Therefore, coalition system increase punishment buyers can impose on sellers and enhance the role of reputation mechanism, and sellers belonging to coalitions are more reliable than sellers belonging to no coalitions.

To make the commitment credible, coalition must enact strict affiliation procedure and regulations. In addition, seller coalitions have more information about their members, so they can mediate and arbitrate disputes more accurately and less costly than other third party enforcement intermediaries.

Seller coalition is very similar to Community Responsibility System (CRS) in medieval Europe (Greif, 2004). CRS was an enforcing institution, whose run is based on collective reputation in community and individual responsibility of community members. CRS made transaction between traders from different cities more personal and facilitate long-distance trade possible.

For Taobao, seller coalition can increase the cohesion of Taobao community, attract more sellers to join Taobao, make sellers be managed by themselves and fight against fraud by monitoring one another. Once fraud happens and is reported to seller coalition, coalition will punish cheaters first and then submit the fraud to administer of Taobao. Therefore, seller coalition can complement the feedback system and reduce Taobao’s cost.

3 Data and variable description

One of the problems with analyzing online C2C transaction like those displayed on eBay and Taobao is the heterogeneity of the products. People sell different products, and, even when the same general identical product type is offered for sale, the condition of the product often varies. Because there is no consistent method to measure product difference, any statistical approach may be problematic. Fortunately, we find a homogeneous product, a prepaid game card of World of Warcraft (WoW), whose transaction is active on Taobao. WoW, developed by Blizzard Entertainment Corporation, is a 3D internet role-playing game. WoW Game players buy virtual prepaid game cards to recharge their game accounts. The process is done through internet: buyers tell sellers their accounts in WoW, and sellers renew buyers’ accounts. If sellers are online, the renewing process needs only several minutes. We choose 300 points card with book value of 15 yuan for our study.

According to Taobao’s product classification categories, we click “*all categories > virtual products of internet games > internet game cards > all zones > online renewing > hour cards*” successively, and then we input 300 as a keyword to refine our search. We can find about 370 game cards(300-points

WoW) displayed on Taobao. The major difficulty in using identical items is finding enough observations. That problem can be addressed by collecting observations over a period, so we collected observations from these game cards twice, from May 30 to 31 of 2006 and from June 8 to June 9 of 2006. Taobao auctions can be 7 or 14 days in length. However, Taobao sellers in our data showed a preference for 7-day auctions. The interval of our data-collecting is 8 days, so we avoid the chance of choosing observations from the same item. We manually collected 364 effective observations in total. For the first time, we collected 161 observations and for the second time we collected 203 observations. To ensure the randomness of data, we did not use any search and exploration methods that Taobao provided. Because the interval between the two collecting periods was 9 days, there were no changing trends in these periods. We can think of these items as identical. We conduct mean and variance tests for the two data sets we collected and find we cannot reject that they come from the same population.

On American eBay, most sellers use English auction to sell their goods, while in China almost all sellers and buyers are used to fixed price auction (eBay Express offers a platform for buyers to buy items by the way of fixed price). Therefore, we choose average sale of a listed prepaid card sold in listing period (from the moment items displayed on Taobao to the moment items sold) (*AverageSale*) as dependent variable. The auction length seller can select are 7 or 14 days, so AverageSale is the quotient of sale divided by the length of auction.

In addition, Taobao provides data of times of listed items clicked by buyers. So we use average click times in listing period (from the moment items displayed on Taobao to the moment items sold) (*AverageClick*) as an ancillary dependent variable to show buyers' browsing habits.

Reputation are measured by feedback score (*Score*), the ratio of positive ratings to all ratings (*PositiveRatio*), and the ratio of negative ratings to all ratings (*NegativeRatio*) respectively. We expect that *Score* and *PositiveRatio* have positive effect on sellers' average sale and *NegativeRatio* has negative effect on sellers' average sale. Our measures of reputation are likely to be somewhat imperfect indicators for one reason: we use feedbacks at the time we collected data rather than feedbacks at the time transaction actually happen to measure sellers' reputation, so there is some measurement error. However, the time interval between data collecting and the close of transaction is very small, only several days, so the potential measurement error is trivial.

On Taobao, transaction rules require that buyers send money to sellers' Alipay account (Alipay is Taobao's online payment tool, similar to eBay's PayPal), and Alipay will inform sellers of buyers' payment. Sellers then deliver items to buyers. In this process, sellers other than buyers have more temptation to cheat, so the problem of C2C transaction becomes a one-sided prisoner's dilemma and sellers' reputation is more important than buyers' reputation.

Different from eBay, Taobao separates members' feedback scores that they acquire as sellers from scores that they acquire as buyers. By this way, Taobao avoids some sellers acquiring high feedback score by buying items with small value. The two variables, *BuyerScore* and *BuyerRatio*, measure sellers' feedback scores they received when they act as buyers and the ratio of positive ratings to all ratings that sellers left when they act as buyers respectively. We expect these two independent variables to have no impact on sellers' transaction.

The cheat of any member of a coalition damages the collective reputation of the whole coalition. To prevent members' reneging or fraud, initiators or organizers must check applicants' identities strictly. If a coalition member cheats, initiators will dispel him or her. Therefore coalition system enhances reputation mechanism. Sellers belonging to coalitions are more reliable than other sellers with the same feedback score but not belonging to any coalitions, and have more chances of being chosen by buyers. The dummy variable *coalition* is 1 if sellers belong to any coalition and 0 otherwise.

Sellers' reputation is so important that some sellers obtain higher feedback scores by feedback manipulation, such as registering multiple accounts (or working with others) in order to exchange feedback, or libel opponents' reputation by leaving defamatory negative feedbacks. To guarantee the integrity of feedback system, Taobao has set up many rules and policies about leaving feedback. Variable *Punishment* is used to measure whether sellers observe these policies or not. The dummy variable Punishment is 1 if sellers violate Taobao's policies and 0 otherwise. This variable is expected to have negative effects on sellers' transaction.

Table 1 presents descriptive statistics for observations. *Score* exhibits great deviation. Its mean is 1 077, but it ranges from a minimum value of 1 to a maximum value of 21 157. The listed prices have small variation. Its maximum value, minimum value, median, and standard deviation are 14, 11, 13 and 0.249, respectively. *PositiveRatio* and *NegativeRatio* have small deviation. The mean of *PositiveRatio* has a mean of 99.86%, maximum value of 100%, and minimum value of 95.45%.

Table 1 Descriptive statistics

Variable	Mean	Median	Max	Min	S. D.
Score	1 077.758	234	21 157	1	1 931.569
PositiveRatio	99.86	100	100	95.45	0.515
NegativeRatio	0.089	0	4.55	0	0.444

(*To be continued*)

(*Continued*)

Variable	Mean	Median	Max	Min	S. D.
BuyerScore	95.514	31.5	1 188	0	172.330
BuyerRatio	96.142	100	100	0	19.255
Price	12.996	13	14	11	0.249
Punishment	0.110	0	2	0	0.347
Coalition	0.063	0	1	0	0.244
AverageSale	1.714	0.158	59.265	0	5.854
AverageClick	8.412	1.892	264	0	26.096

4 Specifications and empirical results

4.1 The impact of sellers' reputation on sellers' sale

In the total sample of 364 observations there were 165 items whose average sale in the listing period was zero. This is because buyers' optimizing behavior leads to corner solutions for some nontrivial fraction of the population; that is, it is optimal to choose a zero quantity. The Tobit model is explicitly designed to model corner solution dependent variables.[2]

AverageSale, *AverageClick*, *Score* and *Price* are all transformed by taking the natural logarithm so that the data would be more normally and it is convenient to consider the elasticities. Because some observations of *AverageSale* and *AverageClick* are smaller than 1, so we add 1 to them before taking natural logarithm.

Table 2 reports regression results for several specifications. Consider *ln(Score)*, *ln(Price)* and *Coalition* first. As expected, the coefficients on these three variables are statistically significant across all OLS and Tobit models and have expected signs. To save space, we do not report other specifications of OLS estimation.

Tobit specifications from model II to model VI indicate that the coefficients on *punishment* are not significant. The reason may be that rules of Taobao are not mature and Taobao always changes its rules, and then buyers do not care about this factor. We can see from model III to model VI that *ln(1+BuyerScore)* and *BuyerRatio* are not significant, which shows that buyers do not care sellers' feedback ratings that they received as buyers. It is appropriate for Taobao to separate users' feedback ratings that they obtained as buyers from that they obtained as sellers.

[2] See Amemiya (1984) for detailed introduction of this estimation method.

Table 2 The determinants of sellers' *AverageSale*

	Dependent variable: ln(1+*AverageSale*)						
Independent variable	OLS	Tobit					
	I	I	II	III	IV	V	VI
ln(*Score*)	0.09***	0.22***	0.22***	0.25***	0.25***	0.25***	0.25***
	(4.67)	(6.24)	(6.18)	(5.85)	（5.70）	（5.74）	（5.73）
PositiveRatio					0.08		
					（0.57）		
NegativeRatio						–0.029	–0.029
						（–0.19）	(–0.18)
ln(*1+BuyerScore*)				–0.06	–0.06	–0.06	–0.06
				(–1.29)	(–1.24)	(–1.27)	(–1.15)
BuyerRatio							0
							(–0.11)
ln(*Price*)	–9.33***	–21.33***	–21.36***	–20.46***	–20.42***	–20.46***	–20.51***
	(–4.82)	(–5.92)	(–5.92)	(–3.65)	(–5.60)	(–5.61)	(–5.58)
Punishment			0.04	0.06	0.09	0.07	0.06
			(0.22)	(0.35)	(0.51)	(0.39)	(0.38)
Coalition	0.35**	0.51**	0.51**	0.57**	0.58**	0.57**	0.57**
	(2.20)	(2.11)	(2.13)	(2.32)	(2.36)	(2.33)	(2.38)
C	23.87***	53.46***	53.55***	51.28***	43.18*	43.18*	51.44*
	(4.81)	(5.82)	(5.82)	(5.52)	(2.56)	(2.56)	(5.47)
Log Likelihood		–393.45	–393.42	–392.60	–392.44	–392.44	–392.58
R^2	0.123	0.104	0.104	0.114	0.115	0.115	0.113
$\hat{\sigma}$	0.711	0.722	0.723	0.720	0.721	0.721	0.722
Left censored obs		165	165	165	165	165	165
Observations	364	364	364	364	364	364	364

Notes: The *t*-statistics are in parentheses. * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.

Sellers' positive ratio and negative ratio can also measure sellers' reputation. We add these two variables (*PositiveRatio* and *NegativeRatio*) into Tobit model and find that they are not significant. This is because WoW prepaid game card has small value and its sale is easy. Item Not Received or Significantly Not as Described problem rarely happens in the process of sale, so sellers can easily get positive ratings and high positive rating ratio and low negative rating ratio. Hence the difference of positive rating ratio and negative rating ratio is small and buyers do not care sellers' positive rating ratio and negative rating ratio.

In mode I of Tobit, a 1% increase in price (starting from the mean values of all variables) causes a $\alpha\beta(1+1\sqrt{AverageSale})$ = 0.503×21.33×(1+1/1.714)≈17.0% increase in sellers' average sale per day.[3] A 1% increase in *Score* (starting from the mean values of all variables) causes 0.503×0.221×(1+1/1.714)≈0.18% increase in sellers' average sale per day. This suggests that a seller, who increases his overall feedback score, doubling it from 1078 to 2156, would on average experience an increase in average sales per day only by 0.31. This is a very small value. Affiliating with coalition(s) causes 0.503×[exp(0.511)–1]×(1+1/1.714)≈52.9% increase in sellers' average sale per day. From the empirical results above, we would see that *Score* has the smallest impact on average sales per day.

Livingston (2005) found that sellers are strongly rewarded for the first few reports that they have behaved honestly, but marginal returns to additional reports are severely decreasing. The sample distribution of the number of positive scores held by the seller in each auction is divided into 5 parts, and dummy variables are created that indicate whether an auction falls into each quartile. *Score1–Score4* take a value of one if the auction is in the second to fifth quartile of overall scores received, respectively. The first to the fifth parts have 21, 70, 91, 91, 91 observations. Regression results are in Table 3. The coefficient on *Price* and *Coalition* are significant as before. The coefficient on *Score1* is not statistically significant, while the coefficients on *Score2– Score4* are statistically significant across all models, with a coefficient size that vary little by models. This means that there is no difference in average sale between sellers whose overall feedback scores are in the part of 11–200 and those whose overall feedback scores are in the part of 201–500.

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[3] It cannot explain coefficients as if these were estimates from a linear regression. We can get Tobit estimates by multiplying linear estimates an adjustment factors, evaluated at the estimates and the mean values. The factor in model I is about 0.503. See Amemiya (1984) for detailed introduction of this estimation method.

Table 3 Marginal effects of overall feedback scores on *AverageSale*

Dependent variable: *AverageSale*				
Independent variable	I	II	III	IV
Price	–10.31	–10.24	–10.22	–10.05
	(–4.78) ***	(–4.74) ***	(–4.73) ***	(–4.65) ***
Coalition	3.35	3.31	3.37	3.74
	(1.83) *	(1.81) *	(1.83) *	(1.99) **
Score1	3.13	3.17	3.23	3.31
	(1.21)	(1.22)	(1.25)	(1.27)
Score2	6.09	6.21	6.23	6.37
	(2.21) **	(2.25) **	(2.26) **	(2.29) **
Score3	9.48	9.61	9.60	10.05
	(3.51) ***	(3.55) ***	(3.54) ***	(3.62) ***
Score4	8.83	8.93	8.93	9.67
	(3.26) ***	(3.29) ***	(3.29) ***	(3.61) ***
Punishment		–0.79	–0.61	–0.45
		(–0.50)	(–0.37)	(–0.27)
PositiveRatio			0.37	0.34
			(0.35)	(0.32)
BuyerScore				–0.003 2
				(–0.99)
BuyerRatio				–0.004 9
				(–0.18)
C	126.19	125.19	85.61	89.33
	(4.51) ***	(4.48) ***	(0.43)	(0.81)
Log Likelihood	–781.052	–780.922	–780.861	–780.347
R^2	0.032 7	0.035 2	0.035 3	0.038 5
$\hat{\sigma}$	5.813 8	5.814 6	5.822 5	5.829 4
Left censored obs	26	26	26	26
Observations	364	364	364	364

Notes: The *t*-statistics are in parentheses. * Significant at the 10% level; ** Significant at the 5% level; *** significant at the 1% level.

Table 4 presents Wald coefficient test of the hypothesis that the higher parts of overall feedback scores have an additional effect on average sale. It is showed that coefficient on *Score2* is significantly different from those *on Score3* and *Score4*. *Score3* and *Score4* dummy variables are not statistically significantly different from each other, suggesting that overall feedback scores beyond 500 have no additional effect on sellers' average sale. Therefore, there are two critical values of overall feedback scores, 200 and 500. Overall feedback scores below 200 have no effect on average sale and beyond 500 have severely decreasing marginal returns to additional positive rating. These results are not sensitive to how the overall feedback scores are categorized.

We conclude here that sellers' feedback score has positive effects on purchasing amounts. However, these effects are severely decreasing.

Table 4 Wald coefficients test of Tobit models

Null hypothesis	Tobit model	
	Chi–square	*P* value
Score1 coef. = *Score2* coef.	4.30	0.038
Score1 coef. = *Score3* coef.	22.87	0.000
Score1 coef. = *Score4* coef.	18.16	0.000
Score2 coef. = *Score3* coef.	4.56	0.033
Score2 coef. = *Score4* coef.	2.99	0.084
Score3 coef. = *Score4* coef.	0.19	0.660
Coeffs. of all part dummies are equal	29.70	0.000
Coeffs. of all part dummies except *Score1* are equal	4.95	0.084

4.1 The impact of sellers' reputation on average click per day

In addition, we use sellers' average click times per day (*AverageClick*) as an ancillary dependent variable to make further analysis. The empirical results are similar to the results when dependent variable is *AverageSale* (Table 2). The coefficients on ln(*Price*), ln(*Score*) and *Coalition* are significant either in OLS or Tobit models. Adding other independent variables to Tobit model, the coefficients on these three variables are still significant. Punishment, sellers' reputation as buyers (ln(*1+BuyerScore*), *BuyerRatio*), *PositiveRatio* and *NegativeRatio* are not significant. To save space, the empirical results are omitted.

4.2 Some speculations on buyers' browsing and purchasing habit

Here we make some reasonable speculations on buyers' click times and purchasing habit according to our empirical results. First we introduce the commodity display on Taobao. Taobao provides several levels of categories, such as *all categories* → *virtual products of internet games* → *internet game cards* → *all zones* → *online renewing* → *hour cards*. Buyers can choose their desired items by clicking these categories. Then buyer can narrow scope further by refining their research by inputting keywords, such as "location" and "price range". Buyer can also sequence listed items by price, ending time or other methods. In the show window, buyers can only observe sellers' ID, prices of listed items, seller's location and time left for items.

We can imagine how a buyer can browse and search on Taobao. If he wants to buy WoW prepaid 300–points card, he will click levels of categories above, and then enter keyword "300". He will find that about 180 items are displayed in the show window. It takes him some time to choose his most desired items.

Except these search and refining methods, only sorting by price is useful for buyers. It is understandable that *Price* is significant in the regression models above. However, when we run regression on *AverageClick*, the two variables *coalition* and *Score* are statistically and economically significant. Since Taobao does not provide powerful search tools for buyers to sort out sellers by reputation and coalition, this finding is puzzling. In addition, buyers can not observe sellers' feedback and whether or not a seller is affiliated with any coalition. Only when buyers click and browse those sellers' items further can buyers observe sellers' feedback and affiliation.

Buyers can sort items by price, but sellers who offer low price are always low–reputation sellers. Hence buyers will not browse items solely by price. If buyers browse items in show window randomly, there are little differences in average click times per day between sellers with high overall feedback score and low overall feedback score, and average click times per day (*AverageClick*) and average sales per day (*AverageSale*) would have no correlation. However, the fact that the correlation coefficient between these two variables is 0.942 implies that buyers do not browse in show window randomly.

Our explanation for these phenomena is that Taobao can not provide a powerful search system and buyers have bounded information processing ability, so buyers put some sellers with high–reputation and reasonable price into their favorites and make preferential transactions with them. Therefore, buyers do not need to take efforts to browse in show window and save their search cost.

Our explanation for the significance of coefficients on *coalition* is that founders of coalitions strictly check applicants' identities to prevent some members' reneging or fraud. Therefore, only sellers' with good reputation can join coalitions. After sellers' entry into the coalition, their behaviors are monitored by other coalition members, so they are more reliable than other sellers with the same feedback score but not belonging to any coalitions, and have more possibility of being chosen by some buyers. We show buyers' browse and search habit in Fig. 1.

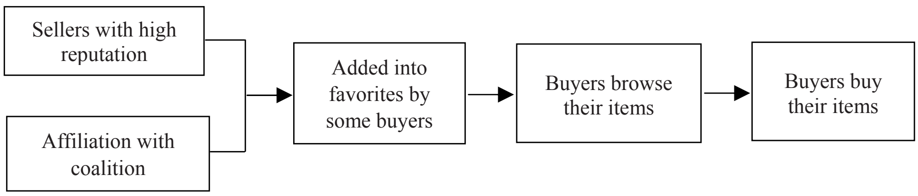

Fig. 1 Buyers' browse and search habit

The facts that buyers put some high–reputation sellers into their favorites and establish a long-term relationship with these sellers imply that internet transaction is not exactly random matching game as simplified by game theory and that repeated transaction accounts for a large proportion of online trade. These mean that buyers can not choose most appropriate sellers within a community and gain more consumer surplus due to the limitation of search tools Taobao provides. With the prevalence of online shopping, the number of sellers and items will be even larger, browsing and searching on Taobao will be increasingly difficult. Buyers can benefit from the extension of market scope only when Taobao improves its search system and reduces buyers' search cost.

5 Conclusions

We collected a virtual prepaid game card of World of Warcraft on the Taobao website. This item is identical and thus we can use it to test the effect of reputation on sellers' trade volume while controlling the impact of heterogeneity. Our empirical results showed that sellers' overall feedback scores and their affiliation status with any coalitions have positive relationship with the average trade volume of each seller's listed items. We also used average click times of each seller's listed item as an ancillary dependent variable to reinforce our conclusion. We found that these two variables were also economically significant. Therefore, we have tested the positive effect of sellers' reputation on seller's transaction.

Furthermore, drawing on our empirical results, we make some reasonable speculations: due to the high search cost, some buyers add high–reputation sellers to their favorites and do a long–term transaction with these sellers. Internet transaction is not exactly random matching game as simplified by game theory and repeated transaction accounts for a large proportion of internet trade. The reason is that buyers have bounded information processing ability and Taobao fails to provide a powerful search system, so buyers cannot choose most appropriate sellers among communities. With the prevalence of internet shopping, the number of sellers and items will be increasingly enormous. Buyers can benefit from the extension of the market only if Taobao improves its search system and reduces buyers' search cost.

WoW prepaid game card is a homogeneous commodity, but it is also a special virtual commodity. Its sale does not need any after service and rarely has any Item Not Received or Significantly Not as Described problems, which implies that sellers can easily acquire positive feedback ratings and high positive feedback ratio. Hence the difference of positive feedback ratio and negative feedback ratio is small and buyers do not focus on sellers' positive feedback ratio and negative feedback ratio. Further studies can use more common products to test the effect of sellers' reputation on their transaction.

In general, we test the role of individual reputation and collective reputation in enforcement under the absence of law and social credit system, and show that private order can substitute public order.

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