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RESEARCH NOTE

FRIENDSHIPS IN ONLINE PEER-TO-PEER LENDING: PIPES, PRISMS, AND RELATIONAL HERDING

De Liu
Department of Information and Decision Sciences, Carlson School of Management, University of Minnesota,
Minneapolis, MN 55455 U.S.A. {liux3269@umn.edu}

Daniel J. Brass
LINKS Center for Social Network Analysis, Gatton College of Business and Economics, University of Kentucky,
Lexington, KY 40506 U.S.A. {dbrass@uky.edu}

Yong Lu
Institute of Internet Finance & Institute of Chinese Financial Studies, Southwestern University of Finance and Economics, CHINA,
and Information Science & Technology, The Pennsylvania State University, 76 University Drive,
Hazelton, PA 18202 U.S.A. {ericlu@psu.edu}

Dongyu Chen
Dongwu Business School, Soochow University, No. 50, Donghuan Road, Suzhou City, Jiangsu Province,
PEOPLE'S REPUBLIC OF CHINA {chendongyu@suda.edu.cn}

Appendix A

The Conditional Logit Model

Let L_{ij} be shorthand for *bidyes*$_{ij}$ and $L_j = \left(L_{1j}, L_{2j}, \ldots, L_{T_j j}\right)$ denote the observed $T\,L_j$ decisions throughout the lifespan of listing j. Suppose k_j of these decisions are positive decisions. Let $d_j = \left(d_{1j}, d_{2j}, \ldots, d_{T_j j}\right)$ be a vector of decisions subject to $\sum_{i=1}^{T_j} d_{ij} = k_j$ and S_j be a set of all such vectors. If we assume the error term ε_{ij} follows an i.i.d. type I extreme value distribution, then the conditional probability is

$$\Pr\left(L_j \middle| \sum_{i=1}^{T_j} L_{ij} = k_j \right) = \frac{e^{\sum_{i=1}^{T_j} L_{ij}\left(x_{ij}\alpha + Y_i\beta + z_{j\gamma}\right)}}{\sum_{d_j \in S_j} e^{\sum_{i=1}^{T_j} d_{ij}\left(x_{ij}\alpha + Y_i\beta + z_{j\gamma}\right)}} = \frac{e^{\sum_{i=1}^{T_j} L_{ij}\left(x_{ij}\alpha + Y_i\beta\right)}}{\sum_{d_j \in S_j} e^{\sum_{i=1}^{T_j} d_{ij}\left(x_{ij}\alpha + Y_i\beta\right)}} \tag{2}$$

Notice that the listing specific effects $Z_{j\gamma}$ cancel out in the conditional probability. This suggests that we can recover the rest of model parameters without knowing Z_j. A conditional logit model estimates the model parameters and by maximizing the likelihood function

$$\ln L = \sum_{j=1}^{n} \Pr\left(L_j \middle| \sum_{i=1}^{T_j} L_{ij} = k_j \right) \tag{3}$$

where n is the number of listings.

Appendix B

Heckman Correction's First Step

Table B1. Probit Regression on the Probability of Being Active

Variables	Coefficients (se)
Log # of past bids by the lender	0.219***
	(0.011)
The lender has past bids	-0.835***
	(0.028)
Log days since the last bid by the lender	-0.537***
	(0.006)
Age of the lender	0.009***
	(0.001)
Gender of the lender (1 = Female)	0.020
	(0.021)
Education level of the lender	0.088***
	(0.009)
The lender is married	0.055*
	(0.022)
The lender's marriage information is missing	0.197***
	(0.034)
# of children of the lender	-0.032*
	(0.015)
# of day since the lender joined the platform	-0.000**
	(0.000)
# of friends the lender has	-0.001
	(0.001)
# of concurrent listings	0.001***
	(0.000)
# of low-risk concurrent listings	0.005***
	(0.000)
Constant	-0.826***
	(0.056)
Log-likelihood	-2491965
Pseudo R^2	0.643
N	2694688

*p < 0.05, **p < 0.01, ***p < 0.001. Month dummies were also included.
Estimated coefficients and standard errors adjusted by sampling weights.

Appendix C

Robustness Checks

To address concerns related to random sampling, we ran the same analysis using two months and five months of data and the results did not change. We also drew different random samples of the data and obtained consistent results across samples.

To make sure parameter estimates are not biased by potential interaction between the pipe and the other two effects, we ran analysis using only potential lenders who are not friends of the borrower and the results did not change.

To address the concern that friendships merely reflect the history of past interactions and have no independent effect, we controlled for past transactions between the borrower and the lender and between the lender and prior lenders in Model 5. Our main results hold after introducing these additional controls.

As an alternative specification, we also ran robust logit regressions with two dimensional clustering by listings and lenders (Table C1, Model 6). This model accounts for correlations among decisions by the same lender but is subject to omitted-variable bias. Besides the controls for conditional logit models, we included several listing/borrower characteristics as controls, such as borrower credit grade, loan purpose, borrowing amount, interest rate, borrower age, gender, education, borrowing history, and authentication. The results are similar to existing ones, although the robust logit reported greater pipe (314.6%), prism (-7.5%), anonymous herding (9.1%), and relational herding (5.0%) effects, which may reflect the omitted-variable bias.

Table C1. Additional Robustness Checks

	Model 6 Robust logit	**Model 7** Weighted Conditional Logit	**Model 8** Conditional Logit on listings with > 25 clicks
# of prior bids	1.091***	1.045***	1.061***
	(0.004)	(0.007)	(0.006)
Lender is an offline strong-tie of the borrower	16.680***	94.650***	38.509***
	(6.290)	(93.806)	(41.866)
Lender is an offline weak-tie of the borrower	7.565***	4.271***	5.529***
	(1.591)	(1.298)	(1.436)
Lender is an online friend of the borrower	3.807***	3.434***	3.692***
	(0.238)	(0.315)	(0.287)
# of prior bids from the borrower's friends	0.925***	0.879***	0.881***
	(0.012)	(0.021)	(0.017)
# of prior bids from offline strong-ties of the lender	1.564***	1.151	0.870*
	(0.080)	(0.089)	(0.057)
# of prior bids from offline weak-ties of the lender	1.143***	1.154***	1.203***
	(0.032)	(0.035)	(0.040)
# of prior bids from online friends of the lender	1.022	0.954**	0.938***
	(0.013)	(0.018)	(0.017)
Log-likelihood	-91339.30	-6317171.4	-21086.6
Adjust R-squared	0.302	0.130	0.156
N	1250426	239444	136745

*p < 0.05, **p < 0.01, ***p < 0.001. All control variables are omitted for brevity. Full results available upon request. Model 6 clusters error by listings and lenders and controls for listing/borrower characteristics including credit grades, loan purposes, interest rate, borrowing amount, listing duration, number of repayments, borrower age, gender, education, past listings, past loans, other loans, identity authentication (via mobile or video), diploma authentication, borrower's number of friends, region dummies.

The lack of a bid from an active lender may be because the lender made an implicit negative decision. As an implicit negative decision does not require a listing's details, including such a case may bias our estimations. The Heckman selection may mitigate such a bias to some extent because the propensity of being active may be correlated with the propensity to evaluate a listing. To further address this potential bias, we ran two additional robustness tests. First, we used the number of clicks on a listing as an "importance" factor for a weighted conditional logit model. The rationale is that a negative decision on a listing with many clicks is more likely an explicit negative decision, thus it should weigh more. Similarly, we also ran analyses on listings with at least 25 clicks (i.e., the mean number of clicks). The two robustness checks yield qualitatively similar results as our main findings (Table C15, Models 7 and 8).

To address the concern that our choice of bid timing may be a source of bias, we constructed a sample using the "last-sight" rule under the assumption that non-bidders repeatedly checked a listing and waited until the last sight to decide not to bid on the list. This alternative data construction depressed some of the coefficients for control variables (e.g., for percentage completed and number of days since listing) but our main findings remained qualitatively the same (results available upon request). Finally, to rule out the possibility that lenders increase their lending probability but decrease lending amount, we ran a fixed-effect model on lending amount while taking into account left-censoring. Our results suggest a positive pipe effect on lending amounts but no significant prism or relational herding effect. Thus our qualitative results do not change after taking lending amount into account.

Appendix D

Correlation Table

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	The lender has bid on the listing	1																		
2	# of days passed since listing	**-.03**	1																	
3	The percentage of funding completed	**.21**	**.12**	1																
4	The listing has reached 100% funding	**.05**	**.13**	**.78**	1															
5	Age of the lender	**.02**	**-.01**	**.00**	.00	1														
6	Gender of the lender (1=Female)	**-.03**	**.03**	**-.01**	.00	**-.08**	1													
7	Education level of the lender	**.02**	**-.02**	**.00**	.00	**.03**	**-.08**	1												
8	# of past bids by the lender	**.15**	**-.10**	**.03**	**-.01**	**.12**	**-.12**	**.12**	1											
9	# of days since the lender's last bid	**-.03**	**.04**	**.01**	**.01**	**-.05**	**.04**	**-.05**	**-.11**	1										
10	Lender and borrower are from the same city	**.03**	**-.01**	**.02**	**.01**	**.00**	**-.01**	**.02**	**.02**	**-.01**	1									
11	# of prior bids	**.27**	**.12**	**.82**	**.63**	**.00**	**-.01**	**.00**	**.05**	**.01**	**.02**	1								
12	# of prior bids from elite lenders	**.17**	**-.07**	**.26**	**.09**	**.02**	**-.04**	**.01**	**.17**	**.02**	**.02**	**.45**	1							
13	# of prior large bids (>=1000 RMB)	**.12**	**.06**	**.53**	**.41**	**.00**	**.00**	.00	**-.01**	.00	**.01**	**.55**	**.08**	1						
14	Lender is an offline strong-tie of the borrower	**.03**	**.00**	**.01**	**.00**	.00	.00	**.00**	**.01**	.00	**.02**	**.01**	**.00**	.00	1					
15	Lender is an offline weak-tie of the borrower	**.04**	**-.01**	**.01**	**.01**	.00	**.00**	.00	**.02**	**.00**	**.02**	**.02**	**.02**	**.01**	.00	1				
16	Lender is an online friend of the borrower	**.12**	**-.03**	**.04**	**.01**	**.01**	**-.02**	**.01**	**.06**	**-.01**	**.01**	**.07**	**.09**	**.03**	.00	.00	1			
17	# of prior bids from friends of the borrower	**.14**	**-.01**	**.30**	**.17**	**.00**	**-.01**	**.00**	**.04**	**.00**	**.02**	**.50**	**.39**	**.36**	**.01**	**.05**	**.11**	1		
18	# of prior bids from offline strong ties of the lender	**.07**	**-.01**	**.05**	**.03**	**.01**	**-.02**	**.02**	**.14**	**-.01**	**.02**	**.07**	**.07**	**.03**	**.01**	**.02**	**.03**	**.04**	1	
19	# of prior bids from offline weak ties of the lender	**.08**	**.00**	**.09**	**.05**	**.01**	**-.01**	**.03**	**.11**	**-.01**	**.02**	**.12**	**.13**	**.06**	**.01**	**.02**	**.04**	**.09**	**.06**	1
20	# of prior bids from online friends of the lender	.17	-.01	.22	.13	.03	-.03	.03	.21	-.03	.03	.31	.30	.14	.01	.05	.14	.23	.08	.14

*Significant numbers (p < .05) are in bold.