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SOCIAL NETWORK EFFECT ON BIDDING STRATEGY ADOPTION IN ONLINE P2P LENDING MARKET

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Abstract

Bidding strategy in online auctions, as a sort of strategic behavior, can help bidders to get what they want more efficiently and effectively. It receives much attention in many researches. However, the determinants of bidding strategy adoption still remain unclear. In this study, we investigate the role of social network in bidding strategy adoption using real transaction data from an online P2P lending market. The analyses reveal that 1) bidding strategy tends to be homogeneous in different online social networks. 2) Joining an online social network does not change the bidding strategy adoption behavior significantly. 3) The size of social network will affect bidding strategy adoption and smaller ones are more homogeneous than bigger ones. 4) In a social network, bidders with different roles have different preferences on bidding strategies. Our findings can be considered as important empirical evidences for theories about social influence and human behavior.

Keywords: social network, bidding strategy, online auction, P2P lending market.

1. INTRODUCTION

Bidding strategy, as a sort of strategic bidding behaviour, can help bidders to get what they want more efficiently and effectively. For example, in eBay, cross-bidding strategy is effective in lowering cost of purchase (Kayhan et al. 2010; Anwar et al. 2006). More importantly, dominant strategy might exist in some types of auctions, like Vickrey (1961) demonstrates that bidding average, rather than revealing bidders' true valuation, is a dominant strategy in second-price sealed-bid auction. It seems that adopting bidding strategy can bring bidders great benefit. We notice that plenty of researchers are devoted to the bidding strategy itself and identify various bidding strategies in real-life auctions (e.g. Shah et al. 2003; Bapna 2004). However, the determinants of bidding strategy adoption are still unclear. Theories in sociology and organization suggest that we consider the impact of group on individuals' behaviours (Foxall et al. 1998; Tirole 1996; Cialdini 1993). Particularly, with the uncertainty of online P2P lending auction, involved parties tend to look for others' behaviours as the guides (Tesser et al. 1983). Furthermore, studies on information diffusion have proved that information flows are geographically localized (Jaffe et al. 1993) and particularly strong in interpersonal network (Singh 2005). In this paper, we are going to explore the role of social network in bidding strategy adoption in online auctions which has been ignored by many relevant studies (Puro et al. 2011; Bapna et al. 2004; Shah et al. 2003; Roth & Ockenfels 2002).

2. THEORY AND HYPOTHESES

Social Influence and Human Behaviour

People usually think that social influence needs "face to face" interaction as a premise in order to affect human behaviour. However, Marsden and Friedkin (1993) point out that social influence does not require such kind of direct interaction. The preconditions are that the information is obtainable and behaviour is observable. Thus, in online activities, though without direct interactions, social influence still has a chance to affect human behaviour. In online digital auctions, Dholakia and Soltysinski (2001) find that many buyers tend to bid for things with more existing bids. The word-of-mouth represented in different forms, like online conversations (Godes & Mayzlin 2004) and online reviews (Chevalier & Mayzlin 2006), shows impacts on product sales. In the research stream about social influence and human behaviour, we argue that introducing the dimension of social network would broaden the research domain. Firstly, we focus on how the attributes of social network affect human behaviour diffusion. Social network structure refers to the way that how individuals are connected. It will critically affect the extent to which a behaviour pattern diffuses across a population (e.g., Granovetter 1973). Leskovec et al. (2007) find that network structure is central to viral marketing. Watts and Strogatz (1998) find that the structure of "small-world" network makes diffusion (e.g., infection of diseases) become more faster than otherwise. Centola (2010) compares clustered networks and small-world networks and find that clustered networks are more helpful in adoption of people's behaviour because the behavioural adoption is different from infection of diseases and requires reinforcement from multiple sources. Social embeddedness is another important factor that needs to be taken into account in investigating social network and human behaviour adoption. Also, social embeddedness describes the degree to which individuals or firms are enmeshed in a social network (Granovetter 1985). Organizational researchers find that social embeddedness is highly relevant to organizational behaviour (Uzzi 1996).

Interaction Breeds Similarity and Similarity Breeds Interaction

Interaction between organizations breeds behaviour similarity. It is interesting to see that frequent communication between two organizations will lead to similar evaluation of strategic issues (Galaskiewicz & Burt 1991). Brass et al. (1998) suggests that organizations compare themselves with, and adopt similar attitudes and behaviours of, those others who occupy equivalent positions in the network. Since, firms' top decision-makers "know one another, see one another socially and at business, and so, in making decisions, take one another into account" (Mills 1956). This phenomenon also implies possibility for sharing important information among those top decision-makers, which lead to similarity in organizational behaviour (Homans 1961). Within a social network, members would have more channels and lower cost to communicate with each other. They would exhibit more homogeneity in bidding strategy adoption. On the other side, homophily principle also implies higher homogeneity within social network. McPherson et al. (2001) also find that people who are friends often exhibit a great deal of similarity in attitudes and behaviours. This is called the homophily in social networks (McPherson et al. 2001) and which is resulted by both social selection and social influence processes (Cohen 1977; Kandel 1978). Blau (1977) states the influence between similarity and interaction is bilateral: interaction breeds similarity and similarity breeds interaction. Building on existing literatures, we assume such kind of information (bidding strategy) exchange activities might also happen in online social network. The principle of homophily has great implication for many aspects of human behaviour, like attitudes they form, information they receive, and interactions they experience.

HYPOTHESIS 1. *Bidding strategy adoption in online social networks tends to be homogeneous to a certain degree.*

Information Diffusion in Social Network

Information for bidding strategy: good or bad, effective or ineffective, how to apply it and etc., are crucial for a bidder in a competitive and uncertain environment. Social relationship may help bidder to get useful information to make decision (Granovetter 1973; Allen 1977) and an individual tends to rely on information coming from his/her social network (Merton 1968; Boudon 1986; Brown 1988), especially in uncertain, novel, or otherwise ambiguous choice situations (e.g. Sherif 1936; Sandell 1999). Abrahamson and Rosenkopf (2012) review theories, build model to explain how social networks channel information about innovations to potential adopters. Besides that, the circulation of information in social network has its own characteristics which would deepen our understanding of human behaviour in social network. Ferrary (2003) point out that in a social network, information about its members circulates very quickly which might create the information asymmetry between members and non-members of the social network. This inspires us to expect that if someone is very successful in auctions by using bidding strategy, then the one within the same social network would aware this more easily and quickly than non-members. Beyond hypothesis 1, we explore the difference in distributions of bidding strategy at market level. Also, one of important properties of social network is its influence on diffusion of technology, opinions and behaviours (Jackson 2009). So, if social network really facilitate the diffusion of certain bidding strategy, we should observe significant difference in bidding strategy distributions between bidders with and without joining a social network. Then beyond hypothesis 1, we explore the differences in the distribution of bidding strategy at market level.

HYPOTHESIS 2. *The strategy distributions of bidders within and without a social network should be significantly different.*

Social Network Size and Homogeneity

Furthermore, in social network theory, homophily in social network (McPherson et al. 2001) should be mediated by network size. Social network theory indicates that keeping all else equal, larger social networks are usually accompanied by lower ability to crystallize and enforce norms (Granovetter 2005). One implication of this statement is that the size of social network will affect bidding strategy adoption.

HYPOTHESIS 3. *Smaller size social network is more likely to be homogeneous in bidding strategy adoption.*

Social Network Member Role and Behaviour

In Prosper.com, a group leader has the full control over the group, including the daily maintenance, inviting new members, screening join requests, helping members to get loan and etc. A group leader has the most access to each member of a group, which means a group leader often has the best position in information circulation within a social network. Another crucial task of the group leader is to serve as a bridge between groups (Burt 2000, p. 360), thereby serving as a conduit to useful information and knowledge located outside the group (e.g., Kotter 1999; Whyte 1943/1993). Building on those statements, we have a hypothesis on the relationship between the role of a bidder and bidding strategy adoption behaviour.

HYPOTHESIS 4. *Bidders with different roles in a social network should exhibit different preferences on bidding strategy adoption.*

3. METHODOLOGY

To evaluate the impact of social network on bidding strategy adoption, at least, we should confirm that social network and bidding strategy are identifiable in our dataset firstly. In this section, at the very beginning, a brief introduction about how Prosper.com works is given. After that, we define bidding strategy with available parameters and identify online social network in Prosper. Particularly, Gini Index will be used to measure the degree of homogeneity of bidding strategy adoption.

3.1 Overview of Prosper

Propsper.com is one of the largest and earliest online P2P lending market in the world. Prosper matches people who need small loans, but can't get them from traditional loan markets mainly hosted by banks and other financial institutions, with willing lenders, and let them communicate directly. The pricing model utilized by Prosper is a multi-unit reverse auction. We downloaded the data used to explore bidding behaviour from Prosper.com on 02/02/2009. The dataset contains listings and all the bids for each listing. The creation date of listings ranges from 11/2005 to 02/2009. The original dataset contained 925,130 listings and 6,550,387 bids. However, parts of the listings are heavily contaminated by noisy data and missing values. We removed observations with missing and abnormal values. For our final clean dataset, the number of listings is 14,958 and the total number of bids for those listings is 133,760.

3.2 Strategy Identification

Research on bidding strategy, has accumulated ample evidences on strategic bidding behaviour patterns. In Table 1, we summarize identified strategies from previous studies for online auctions.

Literature	Market	Strategy
Puro et al. (2011)	Prosper.com	sniping, late bidding, opportunist, evaluator, portfolio bidding, multi-bid strategies(all late), multi-bid strategies(all skeptic), multi-bid strategies(last bid late), multi-bid strategies(stepped bidding), unknown
Bapna et al. (2004)	eBay.com	early evaluators, middle evaluators, opportunists, sip-and-dipper and participator
Shah et al. (2003)	eBay.com	late-bidding (sniping), evaluators, multiple-bid (skeptic and unmasking)
Anwar et al. (2006)	eBay.com	Cross-bidding

Table 1. Identified strategies in online auctions

Each strategy has its own content. Table 2 summarizes those for a clear view.

Strategy	Content
Sniping	Single bid, an extreme case of late bidding strategy (Puro et al. 2011)
Late bidding	Single bid, entry when time close to auction end (Shah et al. 2003)

Opportunist	The late bidding strategy is also called opportunists and has a higher likelihood of winning (Bapna et al. 2004). Made their bids with minimal excess decrements, risk-averse, favor less risky listings (Puro et al. 2011)
Evaluator	Bid once, early, and at a high value, usually significantly greater than the minimum required bid at that time (Shah et al. 2003) Evaluators minimize the time cost of monitoring auctions, may pay more than other winners but gain a risk-aversion premium (Bapna et al. 2004)
Portfolio	Bids are made during the very first seconds of the listing, or bids are made in the same auction at exactly the same second (Puro et al. 2011)
Sip-and-dipper	No descriptive characteristics, several statistical indicators are used to define it, but has a higher likelihood of winning (Bapna et al. 2004)
Participator	Significantly value their time, never bid more than the minimum requirement (Bapna et al. 2004)
Multi-bid strategies (all late)	Number of bids >1, all bids are made within 12 hours before auction end (Puro et al. 2011)
Multi-bid strategies (all skeptic)	Number of bids >1, all of which have zero excess increment (Shah et al. 2003)
Multi-bid strategies (last bid late)	Number of bids >1, only last bid is made within 12 hours before auction end (Puro et al. 2011)
Multi-bid strategies	Bids made within 5 min of each other, max excess decrement> 0.3 pp, last bid is made within 24 hours before auction end (Puro et al. 2011)
(stepped bidding)	Bidder simultaneously monitors several identical auctions, taking advantage of their price differential (Kayhan et al. 2010)
Cross-bidding	Single bid, an extreme case of late bidding strategy (Puro et al. 2011)

Table 2. Strategy content

The parameters used to define strategies are listed in Table 3.

Parameters	Puro et al. (2011)	Bapna et al. (2004)	Shah et al. (2003)
Number of bids made in one auction	yes	yes	Yes
Excess decrement/increment	yes	no	Yes
Time of entry	yes	yes	Yes
Time of exit	no	yes	No
Bid amount	no	Not available in eBay	Not available in eBay

Table 3. Parameters used to define strategy

In table 4, several examples are given to demonstrate the diversity of definitions for bidding strategies employed by different studies.

Literature	Snipping	Late bidding	Opportunist	Evaluator
Puro et al. (2011)	Entry when time left≤30 min	Entry when time left >30 min & ≤12 h	Excess decrement≤0.3 percentage points & time left>30 min	Excess decrement≥1.0 pp & Time left≥1 day Or Excess decrement≥1.0 pp & Time left≥1 day
Bapna et al. (2004)	Not available	Not available	Mean of number of bids=2.45 & mean of time of first bid=1.22 & mean of time of last bid=8.02	Mean of number of bids=1.24 & mean of time of first bid=1.99 & mean of time of last bid=2.53
Shah et al. (2003)	Entry at closing seconds	Entry when time close to acution end	Not available	bid once, early, and at a high value
Roth & Ockenfels (2002)	Entry when time left≤1 min	Not available	Not available	Not available

Table 4. A comparison of definitions for several common strategies

According to previous studies, we define bidding strategies in a hierarchical for the first time and demonstrate them in Figure 1.

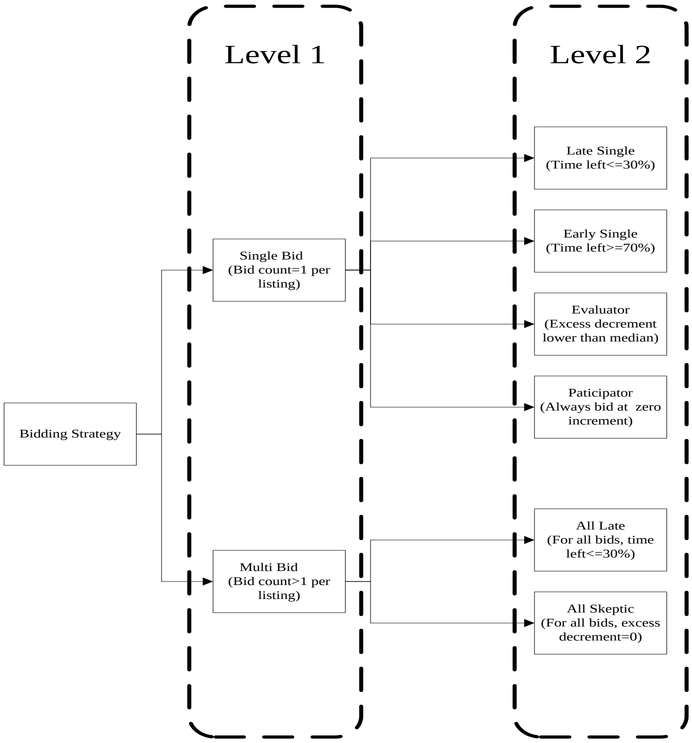

Figure 1. Strategy Definition

Some of the strategy definitions are derived from non-multi-unit auction environments. They need to be modified in multi-unit auction. Since, in multi-unit auction, bid lower or higher than previous bids both have chances to win. In Figure 1, excess decrement/increment is calculated as the difference between current bid interest rate and lowest previous bid interest. If negative, it means current bid interest rate is lower than previous lowest bid interest rates, which is defined as excess decrement. If positive, it means current bid interest rate is higher than previous lowest bid interest rates, which is defined as excess increment. The definitions of evaluator and opportunist are based on excess decrement and excess increment separately. Here we give the quantile for excess decrement and excess increment of all the bids in our dataset.

Quantile	Decrement	Increment
100% Max	-0.0001	0.4500
99%	-0.0005	0.1200
95%	-0.0020	0.0688
90%	-0.0040	0.0500
75% Q3	-0.0095	0.0299
50% Median	-0.0125	0.0145
25% Q1	-0.0247	0.0056
10%	-0.0400	0.0020
5%	-0.0534	0.0010
1%	-0.1000	0.0002
0% Min	-0.2600	0.0001

Table 5. Quantile for Excess Decrement and Increment

3.3 Social Network Identification

In our dataset, we have identified 181 online social networks in Prosper. The summary statistics are listed in Table 6.

Statistics	Value
Number of Social Networks	181
Mean	9
Median	4
Lowest Value	2
Highest Value	140
Std. Deviation	15.51

Table 6. Summary statistics for the size of online social network

From Table 6, we can see that the average social network size is 9 (member). The median size is 4 which indicate that 50% of the social networks are smaller than 4. In Prosper, the largest social network has 140 members while the smallest one only contains 2 persons (social networks only contain 1 person have be excluded from our analysis).

3.4 Homogeneity Measurement

Measuring the impurity of strategy adoption is crucial to verify proposed hypotheses. In this study, Gini Index is employed to measure the impurity of strategy adoption in each online social network.

$$\mathrm{GINI(i)} = 1 - \sum_{j} [p(j|i)]^2 \quad (1)$$

For social network i, j is the number of persons who adopted strategy j. There are two extreme conditions, one is Gini=0, it indicates that, in an online social network only one bidding strategy is adopted. The other is Gini=1, it means that each bidding strategy is equally adopted by the members of this social network.

4. EMPIRICAL RESULTS

We calculate the Gini Index for each social network and get a distribution of it. In order to investigate hypothesis 1, we need to see the dynamic change of Gini distribution with time. At strategy level 1 and 2, we calculate Gini and use ANOVA to analyse its change and get Figure 2.

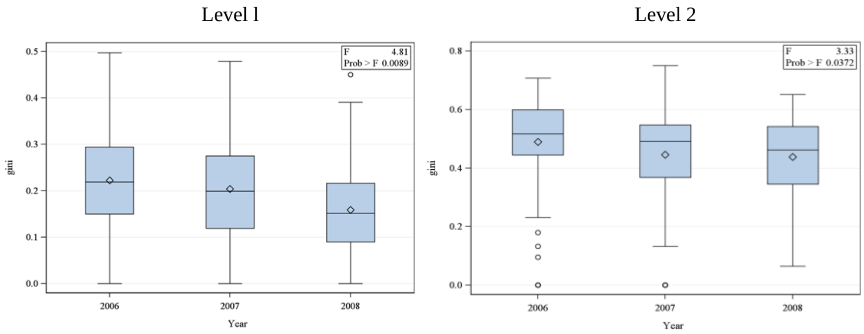

Figure 2. Box Plot for Gini Distributions of Level 1 and 2 Strategies by Years

In Figure 2, we can see the mean of Gini distribution is decreasing year by year. The F statistics are 4.81 and 3.33 and their corresponding p-values are less 0.05. It indicates that the mean of Gini is significantly different for different years and the adoption of bidding strategy tend to be homogeneous.

Hypothesis 1 states that bidding strategy in online social networks tends to be homogeneous to a certain degree. We demonstrate the change of Gini distribution with time in Figure 2 and see a decreasing trend of it at strategy level 1 and 2. Thus, the result presented in Figure 2 shows strong support for hypothesis 1.

Further than Figure 2, we also identify that more and more social networks are converging to single bid strategy (level 1) and late bid strategy (level 2). Within a social network, if one strategy is more popular than the others, we regard it as a dominant strategy in this social network. By counting the number of social networks for each dominant strategy at level 1 and 2, we have Table 7 and 8.

Year	Dominant Strategy	# of Social Network	Percent(%)
2006	Multi Bid	4	3.57
2006	Single Bid	108	96.43
2007	Single Bid	126	100
2008	Single Bid	48	100

Table 7. Dominant strategy and the number of social network (level 1 strategies)

Year	Dominant Strategy	# of Social Network	Percent(%)
2006	All Late	3	2.91
2006	All Skeptic	1	0.97
2006	Early Bid	23	22.33
2006	Late Bid	79	76.70
2007	Early Bid	16	12.70
2007	Late Bid	110	87.30
2008	Early Bid	3	6.25
2008	Late Bid	45	93.75

Table 8. Dominant strategy and the number of social network (level 2 strategies)

To avoid winner's curse (Thaler 1988), auction sites (e.g., Prosper and eBay) suggest bidders to bid only once with their own evaluations. Obviously, most of the bidders adopt such suggestion. Converging to single bid strategy and bid late that can be considered as evidence of market evolution toward maturity. In hypothesis 2, we want to explore the impact of one kind of social connection — joining a social network — on bidding strategy adoption.

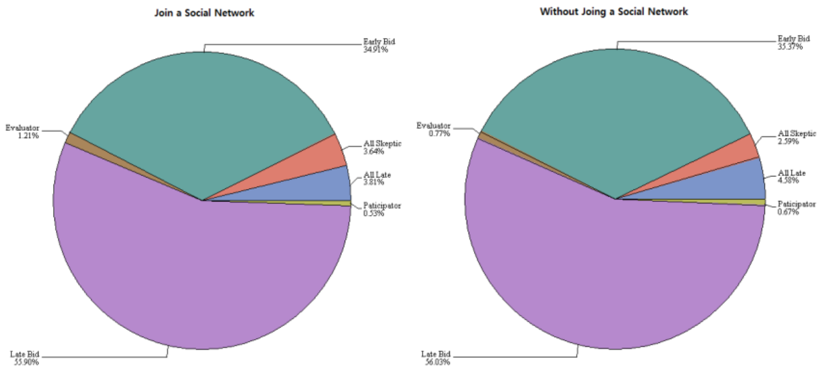

Figure 3. A Comparison for Strategy Distributions with and Without Joining a Social Network

In Figure 3, we cannot identify any significant difference in two pie charts. At least, we can conclude that, at market level, whether joining a social network or not do not show any significant difference in bidding strategy distribution.

Hypothesis 2 postulates that the strategy distributions of bidders within and without a social network should be significantly different. However, it does not receive any support from Figure 3. On average, joining a social network does not change the bidding strategy distribution. It means whether joining a social network or not does not impose any significant impact on bidding strategy adoption.

In hypothesis 3, we will investigate one of the determinants proposed by previous study (Granovetter 2005) to Gini variation. Firstly, we divide 181 social networks into 3 categories according to their size.

Social Network Size	Frequency	Portion(%)	Category
[2,3]	79	43.65	Small
(3,10]	70	38.67	Medium
(10,140]	32	17.68	Large

Table 9. Categorized social network by size

To see how bidding strategy adoption homogeneity changes with social network size (hypothesis 3), we test our hypotheses with ANCOVA on Gini versus social network size adjusting for covariate year. Figure 4 and Table 10 are the estimated results.

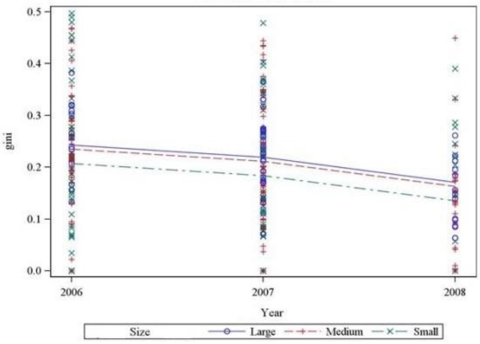

Figure 4. Scatter Plot for ANCOVA

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	0.1353	0.0204	6.64	<.0001
Year=2006	0.0718	0.0208	3.44	0.0007
Year=2007	0.0487	0.0202	2.41	0.0166
Size=Large	0.0357	0.0198	1.8	0.0727
Size=Medium	0.0279	0.0158	1.77	0.0785

Table 10. Parameter estimates for ANCOVA

Hypothesis 3 reasons that social network with smaller size is more homogeneous than bigger ones. From Table 10, we can notice that, in any year (keeping covariate year fixed), the size of social network imposes statistically significant impact on bidding strategy adoption homogeneity: the size of social network is positively related to Gini (comparing with the reference group size=Small, the estimated results for size=Medium and size=Large are 0.0279 and 0.0357 and both p-values <0.1). It indicates that smaller size social network tends to be more homogeneous in strategy adoption. Thus, hypothesis 3 is proved.

To verify hypothesis 4, we group bidders' role into 3 categories: Bidder Only, Group Leader and Member Only. Table 11 is a summary for the relationship between bidding strategy adoption and bidders' roles.

Parameter	Bidder Only	Member Only	Social Network Leader
All Late	3.9295%	4.8128%	3.7607%
All Skeptic	3.1407%	2.2626%	3.7159%
Early Bid	34.2525%	34.7158%	37.6299%
Evaluator	1.0411%	0.6525%	1.1701%
Late Bid	57.0070%	56.7258%	53.6224%
Paticipator	0.6292%	0.8305%	0.1009%

Table 11. Role and bidding strategy adoption

From Table 11, we can find that, among social network leaders, the portions of “All Skeptic”, “Early Bid”, and “Evaluator” are much higher than other roles. And strategies “All Late”, “Late Bid” and “Participator” are not frequently employed by leader as other roles.

Hypothesis 4 is about bidder’s role in social network and its potential impact on bidding strategy adoption. According to Table 11, we notice that, comparing with roles bidder only and member only, a social network leader prefers strategies “All Skeptic”, “Early Bid”, and “Evaluator” to “All Late”, “Late Bid” and “Participator”. This can be considered as a supportive evidence for hypothesis 4.

5. CONCLUDING REMARKS

Despite a vast majority of studies focus on identifying bidding strategy, very little attention has been paid to the determinants of bidding strategy adoption. In this study, we focus on the perspective of social network and find theory support from the research stream about social influence and human behaviour. Several hypotheses are derived from previous theoretical works and are summarized in Table 12. Real transactional and relational data from Prosper.com is used to verify those hypotheses.

Hypothesis	Hypothesis Content	Theory	Verification
1	Bidding strategy adoption homogeneity trend at market level	Social network homophily (McPherson et al. 2001)	Supported
2	Bidding strategy adoption distributions comparison between social network members and non-members	social network and information diffusion (Jackson 2009)	Not supported
3	The impact of social network size on bidding strategy adoption homogeneity	Social network size and ability to crystallize and enforce norms (Granovetter 2005)	Supported
4	The impact of social network role on bidding strategy adoption	Group leader role in channelling information (Burt 2000, p. 360; Kotter 1999; Whyte 1943/1993)	Supported

Table 12. Summary for hypotheses

At present, we only focus on the impact of social network on bidding strategy. However, this is not as ideal as we preconceived. In order to evaluate the impact of social network on bidding strategy adoption more precisely, we will expand our research by introducing more control variables, like bidders’ experience and physical locations. More theory analysis will also be included in future work to explain the empirical results more thoroughly.

6. ACKNOWLEDGEMENTS

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