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Network vs Market Relations: The Effect of Friends in Crowdfunding

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***Abstract*—Crowds offer a new form of efficacious collective decision making, yet knowledge about the mechanisms by which they achieve superior outcomes remains nascent. It has been suggested that crowds work best with market-like relationships when individuals make independent decisions and possess dissimilar information. By contrast, sociological discussions of markets argue that risky decisions are mitigated by network relations that embed economic transactions in social ties that promote trustworthiness and reciprocity. To investigate the role of networks within crowds and their performance effects, we examined the complete record of financial lending decisions on Prosper.com, 1/2006-3/2012, the first U.S. crowdfunding platform and a chief gateway to capital for entrepreneurs and general borrowers that continues to disrupt conventional financial lending structures infusing more than $5.1 billion into the market in 2013. Our study reveals how reciprocity, recurring borrower-lender dyads, and persistent co-lending underpin the dynamics of network lending. Further, we show how network ties influence the evolution of the lending behavior. We find that in the early stage of fundraising, network relations provide larger proportions of loans, typically lending four times more per bid than strangers. They also respond to loan requests on average 59.5% sooner than strangers. The size of the first loan and the time to lending also tend to prompt lending by strangers, suggesting that network relations might move the market, a finding that persists even as fewer lenders dominate more of the market for loans on Prosper. Finally, network relations are associated with greater engagement: when the first loan is underwritten by a friend, 50% of the remaining loans come from friends as well.**

Keywords—peer-to-peer lending; crowds; networks; decision-making; bidding dynamics; emerging markets

I. INTRODUCTION

These are the days of the collective when institutions are slowly being supplanted by competing services provided by crowds. Uber is challenging medallion-touting taxis, malls are losing the race to online retailers, cable is at loggerheads with 'cordcutters', and there is a widespread movement recognizing that people need banking, but not banks. This last phenomenon is particularly disruptive—crowdfunding infused more than $5.1 billion into the global financial markets in 2013 [1] and since then it continues to provide reliable banking alternatives against traditional banking establishments [2,3]. This emergent phenomenon requires specific efforts to explain, as it is still not well understood, whether its underlying mechanisms reinforce or contradict traditional economic models.

In this paper, we investigate the effect of network relationships, or friendships, in crowdfunding. Our study of data spread over more than six years from the first peer-to-peer lending organization in the U.S. called Prosper [4] shows that lenders who are friends of borrowers, are important especially in the early stages of fundraising. Finance literature suggests that these individuals may have special insight into the creditworthiness of a proposed project and could promote trustworthiness [5,6,7,8]. However, they might also contribute to a misallocation of resources by systematically favoring friends' projects [6,7]. We approach this debated problem empirically by analyzing the structure and usage of network relationships in the larger crowd of strangers. We also address the possibilities and limitations of using these strategic friendship ties for fundraising throughout the evolution of the platform.

Prosper is one of the largest crowdfunding platforms in the U.S. [2]. It deploys a peer-to-peer marketplace model, allowing people to invest in each other's projects in the form of personal loans. The borrower posts her project proposal on the online platform for an amount between $1,000 and $25,000. A set of lenders assess the project's merit and *bid* to fund a fraction of this amount based on their own idiosyncratic criteria and baring the entire risk for their investment. A loan is issued only if the borrower manages to raise her target amount. The data we use compiles details about over 1.3 million members registered between the inception of the platform (January 2006) and March 2012[1]. Throughout this time, 65K lenders bid on 236K projects of 129K borrowers for a total of over $774 million. Of this, the actual amount loaned was around $318 million.

The remainder of the paper is organized as follows: Section II summarizes related research in crowdfunding and establishes the uniqueness of our analyses in relation to existing studies. Section III starts off by investigating the effect network relationships have on early bidding. Then, it details our analysis that focuses on how reciprocity and recurring collaborations underpin the dynamics of network relationships. Eventually, it addresses the interplay between network relations and strangers in the crowd over the

[1] This year marks the appearance of algorithmic investment services such as LendingRobot [9], which provide lenders automated ways to bid based on pre-selected criteria. These algorithms have thus become popular after the time period we are investigating here and they should not affect our results.

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evolution of Prosper from its inception to its current state. Discussions and conclusions are in Section IV.

II. Related Work

By purportedly bypassing credit constraints posed by traditional forms of capital infusion, crowdfunding has attracted wide attention from media, entrepreneurs, socially minded initiatives, NGOs, and most decidedly, from banks (cf. [2]). Most of the academic work on the topic focuses on the factors associated with the success of a project proposal. Studies based on data from Prosper, Kickstarter, Kiva, DonorsChoose, and Sellaband have gathered evidence for the predictive power of factors such as project quality [10], language of the request [11], geographic embeddedness [12], herding behavior behind the temporal progression of bidding [13], project updates during the running time of the proposal [14], as well as personal networks on social media platforms [15]. This body of work has greatly illuminated our understanding of the new phenomenon of crowdfunding and geared our focus towards the network aspects of peer-to-peer lending.

Literature indicates that supportive communities lead to lower and less exploitative interest rates [16], provide feedback during the elaboration of new project proposals [17], and are responsive to promotional campaigns on social media [18]. As opposed to platforms like Kickstarter, Prosper does not enable linking social media accounts (such as Facebook and Twitter) to the membership to locate a lender's or borrower's complete social network. Instead, it allows its registered users to self-report publicly visible friendship network ties. These more formal ties and the resulting stronger and better verifiable network may have helped project assessment in the nascent stage of the platform [8] and may have also contributed positively to the project outcome [19].

Drawing comprehensive data from Prosper, we collected information for the first six years of the platform's existence. Based on this data, we extend these studies by analyzing the specifics and functioning of the Prosper friendship network and by gauging the effect of friends on the bidding process over time. To the best of our knowledge, none of the existing studies have addressed the interplay between friend-aided fundraising and other market players.

III. Results

Essentially, the temporal progression of bidding is predictive of the outcome of a project proposal [13]. This fact is indicative of a herding behavior which drives the bids and might result in a misallocation of resources. It is also known that the borrower's social capital on the platform is associated with a higher likelihood of her project being funded [15,19]. Inspired by these two findings, we look at friends as first bidders on one's loan request.

Figure 1A shows the difference in the time elapsed until the first bid is placed between the case when the borrower and first bidder are friends (purple, upper panel) and when they are strangers (green, lower panel). Accordingly, the probability that a friend places a first bid *within less than* 10% of the total running time of the project proposal is 0.71, instead of 0.6 if she is not a friend of the borrower. Depending on the total running time of the proposal, 10% correspond to 1–1.5 days after posting. This finding indicates that friends may be quicker in assessing and trusting a loan request as compared to strangers. Furthermore, the bimodal distribution of the time-to-bid in the case of strangers suggests the presence of two types of lender-strangers: leaders (those who bid early when assessing the creditworthiness of the borrower may be difficult) and followers (those who bid at the time when the creditworthiness of the borrower is most apparent). These categories of leaders and followers are reflective of more general patterns found on other crowd based platforms like Kickstarter [18] and eBay [20].

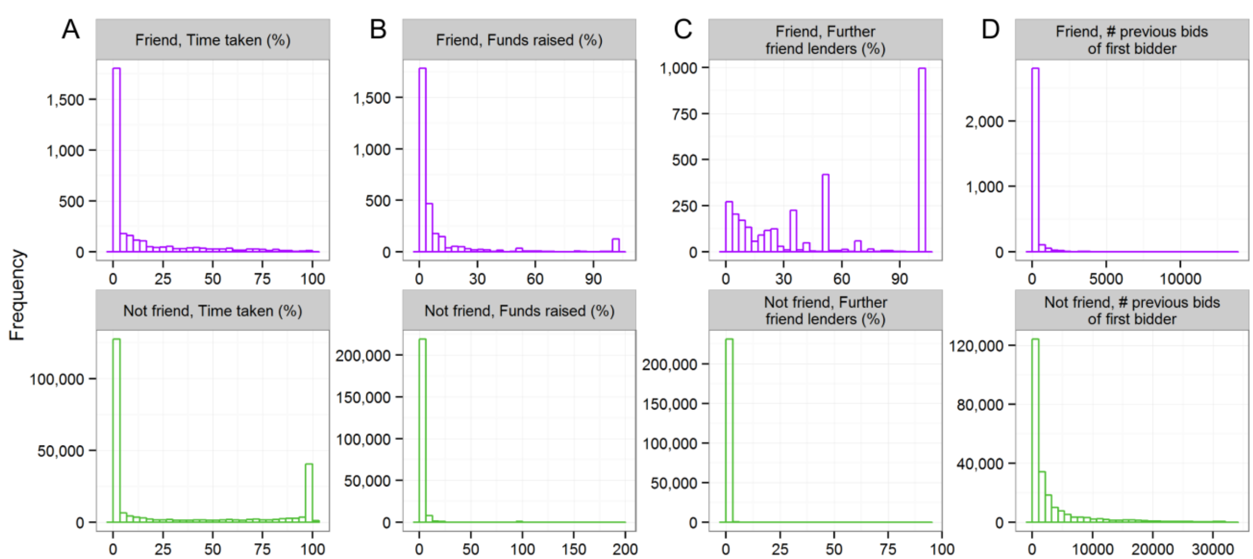

Figure 1 Characteristics of the first bid if the lender is a friend of the borrower (purple, upper row) as opposed to when she is not (green, lower row). Histograms show the frequency of certain values for (A) the time until the first bid is placed as a percentage of the total running time of the project proposal; (B) the bid amount as a percentage of the total requested amount; (C) the percentage of lenders who bid subsequently and are friends of the borrower; and (D) the number of bids the lender who bids first placed before this particular bid.

In addition to reacting to a loan request faster, friends invest a considerably larger percentage of the requested amount than stranger first-funders. The probability that the amount offered by a friend *exceeds* 10% of the total amount is 0.17, while the likelihood that the funds given by non-friends are larger than the same percentage is only 0.03 (see Figure 1B). Due to a subsequent herding mechanism [13], the time-to-bid and the size of the first bid are associated with significant changes in the entire subsequent bidding process. Following lenders are more likely to bid on and fully fund proposals that appear popular with other bidders[2]. Moreover, as shown on Figure 1C, the presence of a friend first bidder activates further friends throughout the bidding process. The percentage of friend bidders is on average 50.2% (standard deviation 38.66) when the first bid comes from a friend as opposed to 0.11% (standard deviation 1.72) when it does not come from a friend.

Figure 1D indicates that when accounting for the experience of the lenders quantified in terms of the number of bids placed before the analyzed bid, first bidder friends have been less active on the platform. While the probability of an average lender bidding *more than* 100 times before the considered project proposal is 0.87, a friend of the borrower bids at least this frequently much less often, i.e., only in 1/4 of the cases. For nearly 500 friend first-bidders, their bid represents the first ever on the platform, suggesting that network relations are associated with increasing lender engagement. Differences between the distributions for friends and non-friends are in all four cases significant (Whitney-Mann test $P<2,1\cdot 10^{-4}$ and Kolmogorov-Smirnov test $P<10^{-16}$, two-tailed hypothesis).

Note that the results presented so far pertain to the very first bidder. Figure 2 shows the changes in the funds raised and the time-to-bid for the first 20 bidders differentiating between friends and strangers. Accordingly, as the bidding process progresses, friend-bidders remain more generous than strangers (left panel). The cumulative probability that the funds raised are above 10% of the requested amount is consistently higher if the borrower and lender are friends than if they are not. In terms of the time-to-bid, the trend is reversed after the first bidder. As shown in the right panel of Figure 2, according to the cumulative probability that the bid occurs within less than 10% of the total running time friend-bidders are overtaken by a crowd eager to invest, starting with the third bid. Given the general associations between network relations and lender/borrower crowdfunding dynamics, next we analyze the structure and functioning of these network relations.

A. The Prosper friendship network

The Prosper friendship network (38,222 undirected edges between 63,223 members) features 25,001 components with a star graph structure [21, p. 543]. Figure 3A shows an illustrative component with a single central *hub* member. This topology is typical of brokerage in social networks [22]. Members can adopt the role of borrower, lender, or both at some time point during the six years with the most prevalent roles being borrower and lender. The same member being both a lender and borrower is less common, but very interesting since this can widen the base of reciprocity in a relationship. We will explore this aspect in the section *Network ties over time*.

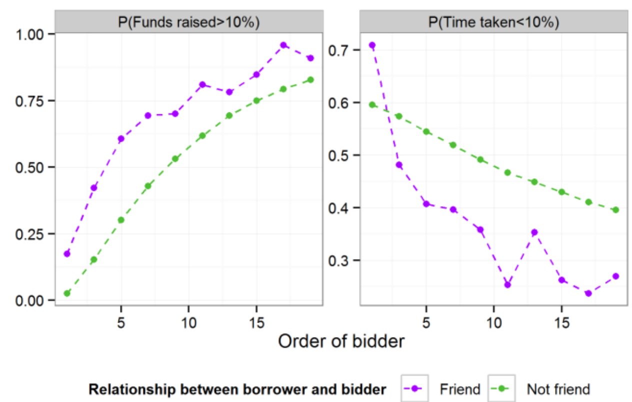

Figure 2 Progression of the bidding process. Shown are the characteristics of the first 20 bids averaged over all projects. Cumulative probability that the funds raised are larger than 10% of the total requested amount (left panel), and that the time-to-bid is smaller than 10% of the running time of the project (right panel). Data for friend bidders is shown in purple, for strangers in green.

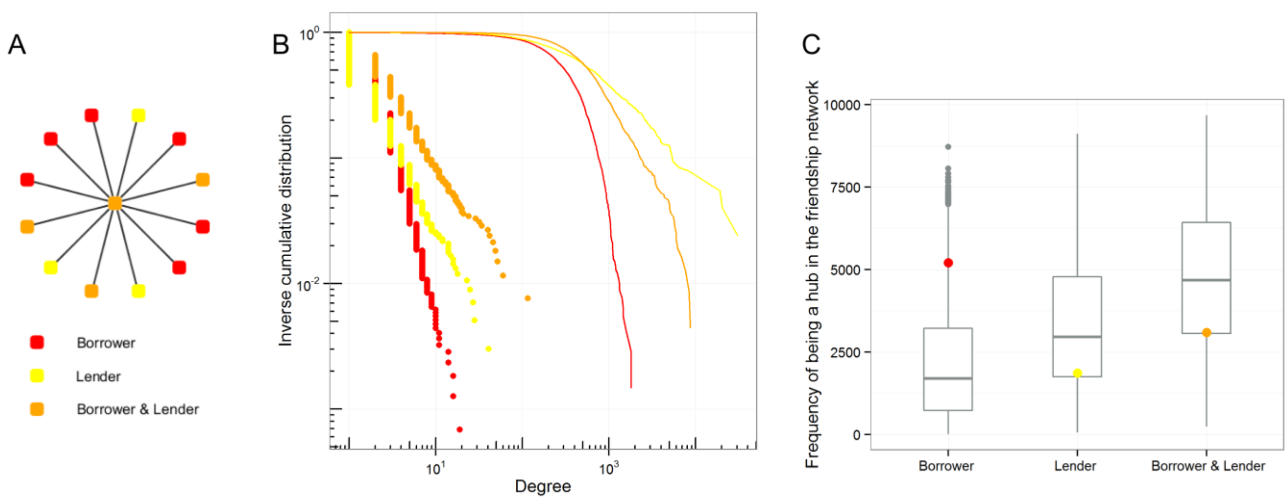

Figure 3 Exploration of the Prosper friendship network. (A) Exemplary excerpt of the network featuring members in three different roles: borrowers (red), lenders (yellow), and members with dual role who both lend and borrow (orange). (B) Inverse cumulative distribution of the members' degree in the friendship- (dots) and bidding network (lines). Distributions are color-coded according to the different roles. (C) Occurrence of members with the specific roles as hubs of the components: observed frequencies (dots) are laid over the sampled distributions, which are based on 10,000 randomized networks (boxes).

Figure 3B (dots) indicates that the degree distribution of the members in the friendship network differs based on role. We plot the fraction of members having a given degree or greater for each of the roles separately. Borrowers tend to have a lower degree than lenders, who have a lower degree than dual role members. Given the advantages of friend bidders, borrowers have a strong incentive to initiate friendships. Lenders might have less motivation to make friends, but see better chances due to the funds they provide. The combination of these two rationales (increased interest alongside a privileged situation) might intuitively explain why members with dual role end up having more friends than any pure category. These differences between the structural roles are related to the activity of borrowers, lenders, and both. Consider the *unweighted* bipartite network N of lenders L and borrowers B, in which each of the connections E represents an existing individual bid regardless of the offered amount:

$$N = (L \times B, E) \tag{1}$$

Note that this network is only formally bipartite since $L \cap B \neq \emptyset$ due to the members with a dual role. In N, borrowers have comparatively the lowest number of bids contributing to their projects, while lenders cover a much broader range by bidding up to more than 30K times (see Figure 3B, lines). Members with dual role are confined between the two. This shows that their total activity defined as the sum of their degree as lenders and their degree as borrowers (i.e., the number of investments added to the times they received funds) is bounded by the actions of pure borrowers and lenders.

Finally, we address the question whether any of the roles is associated with a hub (or broker) position in the friendship network. There are η_P^b=5,210 borrowers, η_P^l=1,863 lenders, and η_P^{bl}=3,097 members with dual role who are hubs in the Prosper network. To establish the uniqueness of these numbers given the network structure, we perform a permutation analysis [23, p. 154–156]. The goal is to obtain reference distributions for the occurrences η_P^x, $x \epsilon \{b, l, bl\}$ observed on Prosper. Based on these distributions we can then distinguish significant role-position associations from expected ones. Let $\mathcal{H}$ denote the set of all networks G that have the same topology and the same number of nodes in one of the three roles as the Prosper network G_P:

$$\mathcal{H} = \{G : T(G) = T(G_P) \land R(G) = R(G_P)\}, \tag{2}$$

where the topology T refers to the number of nodes, number of edges, the degree distribution, and the entire connection structure of the graph, while R denotes the number of nodes having the individual roles. We generate a sample of $\mathcal{H}$ from G_P by keeping T and R fixed and reassigning the roles of the nodes randomly. After creating a sample of 10,000 randomized networks G, in each network we count how often members with different roles are hubs. Based on the set of these values

$$\{\eta_G^x | G \epsilon \mathcal{H}\}, \tag{3}$$

we assess the statistical significance of the occurrences η_P^x observed in the Prosper network using the *z*-score which is defined as:

$$z^x = \frac{\eta_P^x - \langle \eta_G^x \rangle}{\sigma(\eta_G^x)}, \tag{4}$$

where $\langle \eta_G^x \rangle$ denotes the sample average, $\sigma(\eta_G^x)$ denotes the sample standard deviation, and $x \epsilon \{b, l, bl\}$ corresponds to the different roles. Figure 3C shows the observed occurrences η_P^x as dots and the summaries of the distributions of $\{\eta_G^x | G \epsilon \mathcal{H}\}$ as boxes. As opposed to lenders and members with dual role, borrowers are hubs more often than expected based on the sampled distribution (z^b=1.84 corresponding to P=0.03, one-tailed).

Briefly, our investigation shows that the Prosper friendship network has a unique structural signature. Members with dual role have more friends than borrowers or lenders, but borrowers are more likely to possess brokerage positions in the network and to enjoy their apparent benefits in the bidding process. In the next section, we look at the evolution of these relationships.

B. *Network ties over time*

As we have seen before, Prosper's friendships have a high activation potential and are an important determinant of early bidding. This raises the question of whether these initial advantages provided by network ties are sustained or taper off with time. To explore the dynamics of network ties in the Prosper crowd, we ask the following three questions:

1. How prevalent are reciprocal bids? In other words, how likely is it that a borrower who received funds from a lender will offer her money in support of her project at a later point in time?
2. Are network ties especially enduring? Namely, is the same lender bidding repeatedly on the same borrower's project?
3. Do pairs of lenders tend to fund the same projects?

We start by tackling the first question and investigating reciprocal bids. The pervasiveness of members with dual role indicated that friends might support each other mutually by taking on alternatively the roles of borrower and lender (Figure 4A, inset). To determine this, we use a measure known in the network science literature as *reciprocity*. Reciprocity quantifies the probability that two nodes have mutual ties to each other [24, p. 124–125]. Specifically, the reciprocity r equals to the ratio of ties pointing in both directions E^{bidir} to the total number of edges E: $r = E^{bidir}/E$. The bipartite bidding network N_{NF} constructed out of the 9.7 million bids between lenders and borrowers who were *not* friends on Prosper has a reciprocity of r_{NF}=7.57·10^{-5}. On the other hand, for the network N_F constructed out of the 15.5K bids between friends, r_F=0.05. The latter means that if a member m_1 with dual role bid on the project of her friend m_2 who is another member with dual role, then there is a 5% probability that m_2 will bid

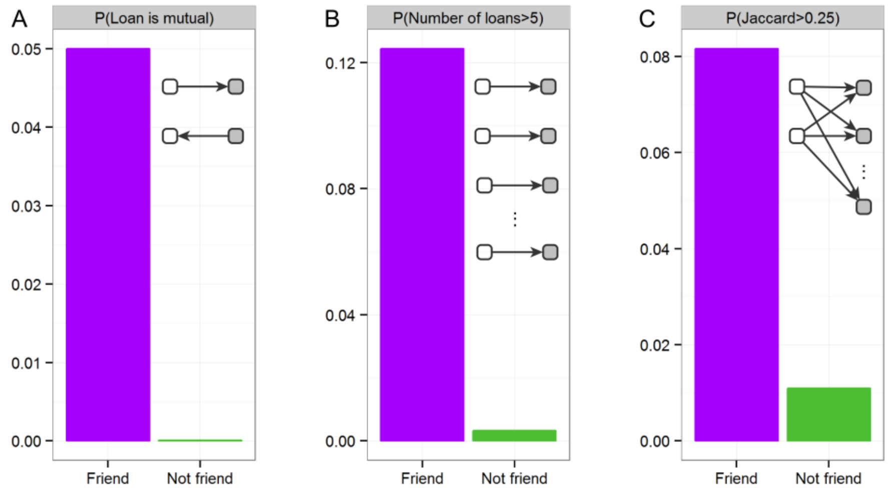

Figure 4 Patterns which are more common in network lending (purple) than in the crowd (green). (A) *Reciprocity*: probability that a loan is mutual. (B) *Recurring dyads*: chances that a lender bids more than 5 times for the same borrower's projects. (C) *Repeated co-lending*: normalized frequency of two lenders providing funds to the same borrowers. Specifically, we show the probability that the Jaccard coefficient computed for the bids occurring after the two lenders funded the same borrower for the first time is greater than 0.25. Insets illustrate the network patterns with the direction of edges indicating the flow of funds.

on m_1's proposal as well at some point. As summarized in Figure 4A, this shows that friendships do entail returned favors on Prosper.

Second, repeated lending to the same borrower is also more probable if the two parties are friends. Figure 4B shows that the probability that a lender funded the same borrower more than 5 times is about 12 times higher if lender and borrower are friends (purple) than when they are strangers (green). The plot is based on the distribution of the number of bids in the two cases, which are significantly different (Whitney-Mann test, $P<10^{-16}$). While the median number of bids for a lender friend of the borrower is 2 (interquantile range 2), a lender who is not friends with the borrower bids typically just once (interquantile range 0). This indicates that recurring borrower-lender dyads are indeed more common in the presence of network ties.

To address the third question, we investigate long-term pairwise collaborations between lenders. Specifically, we compare the events that follow a spontaneous co-lending with those occurring after a co-lending that is augmented by friendship ties. In our context, co-lending means that a pair of lenders l_i and $l_j \in L$ funds the same borrower: $\exists b \in B: b \in \Gamma(l_i) \wedge b \in \Gamma(l_j)$, where $\Gamma(l)$ denotes the set of borrowers funded by lender l. To quantify co-lending over time, we use the Jaccard coefficient [25], which is defined as the number of borrowers both lenders l_i and l_j supported, divided by the number of unique borrowers funded by either of them and takes a value between 0 and 1:

$$J(l_i, l_j) = \frac{|\Gamma(l_i) \cap \Gamma(l_j)|}{|\Gamma(l_i) \cup \Gamma(l_j)|}. \quad (5)$$

Figure 4C is based on the relative frequencies of the Jaccard coefficients computed *after* a first co-lending event[3]. The purple box is computed for the case when two lenders co-lent in the first instance to a borrower who they are both friends with. The green box is based on randomly chosen pairs of lenders who provided funds to the same borrower *without* such friend ties. Accordingly, the probability that the Jaccard overlap between two lenders is larger than 0.25 is about 8 times higher in the presence of network ties. There are 74 lender pairs who supported exclusively their friends. Thus, in addition to shared lender preferences, repeated co-lending might also be fueled by common borrower friends. The initial co-lending events probably reflect the strategic efforts of borrowers to rein in friends and encourage them successfully to bid for their projects. Co-lending is especially noteworthy in this context since network relations that are predicated on the necessities of borrowers might require later sustained efforts to generate repeated patterns with lenders. Finally, note that the Jaccard coefficients computed over the entire time period for a set of lender pairs chosen uniformly at random (in this case an initial co-lending is not required) show extremely low values confined between 0 and 0.07.

In summary, we find that friends tend to reciprocate bids among each other more often than strangers do and that lender-borrower dyads are more likely in the presence of network ties. Furthermore, lenders show a tendency for co-lending to the same borrowers after having supported a common friend.

[3] The data used for this plot contains the activity of the lenders who have bid at least three times throughout the six years period. The result is unaltered by the presence and the value of this small cut-off.

C. Interplay between network and market ties

Viewing Prosper as an emerging market, we now assess the involvement of friends throughout the evolution of the platform. Figure 5 shows the progression of their market share between 2006 and 2012[4]. The market share m of a certain group C within a timeframe t is calculated as the percentage of the total amount lent that comes from the members of the given group:

$$m(C) = \frac{\sum_{l \epsilon C} a_l^t}{\sum_l a_l^t} \cdot 100, \tag{6}$$

where a_l^t denotes the amount bid by lender l during time t. On the monthly aggregate, there is a trend towards the increasing involvement of friends of the borrowers starting in 2007 (see Figure 5, upper panel). This engagement declines in 2010 and practically vanishes in 2011 indicating a "crowdfunding fatigue" among friends. One of the potential explanations is that friends become overwhelmed with requests to fund projects beyond their possibilities. Note that there is a prominent outlier in June 2010, which can only be explained by big lenders supporting their friends. Next, we focus on the activity of these big lenders.

We show their contribution in the bottom panel of Figure 5 through the top 2% of the lenders who offer the highest loans (hereafter the *elite*). Let $<_{a^t}$ be an order defined on the set of lenders based on the total amount a they lent over time t as:

$$l_i <_{a^t} l_j \Leftrightarrow a_{l_i}^t > a_{l_i}^t, \tag{7}$$

Based on this order, we can define the set of elite lenders ε in the top p percentile as follows:

$$\varepsilon = \left\{ l \in L : r_{<_{a^t}}(l) \geq \frac{p}{100} \cdot n(t) \right\}, \tag{8}$$

where $r_{<_{a^t}}(l)$ denotes the rank r of lender l according to the order $<_{a^t}$ and $n(t)$ denotes the number of lenders at time t. We focus on the top 2% of the lenders for each year, i.e. p=2 and t corresponds to one calendar year.

Before 2009, we see periodic changes in the market share of the elite. The relatively low percentages in December 2006 and 2007 versus the local maxima for the month of June of the respective years indicate seasonal differences. After 2009, the market share of the elite doubles within 2.5 years. This reveals a shift towards a monopolist financial system dominated by a few powerful lenders, as opposed to a more eclectic and egalitarian arrangement. This tendency is reflective of the larger financial market trends: since the repealing of the Glass-Steagall act, approximately 45 large banks in the U.S. have merged repeatedly, resulting in just four banking behemoths (JP Morgan Chase, Citigroup, Bank of America, and Wells Fargo) by 2015 [26].

[4] Note that Prosper stopped reporting its activity between November 2008 and April 2009.

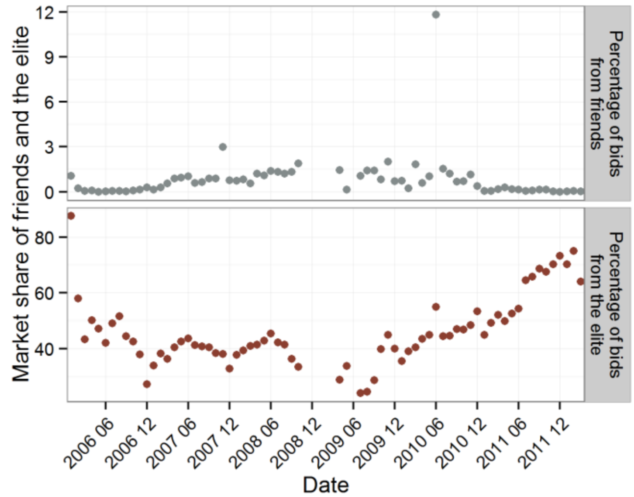

Figure 5 Changes in the market share of friends and the elite over time. Data points represent monthly averages.

On a final note, we go back to the outlier of June 2010. In this single month, 5 elite lenders supported 13 of their borrower friends with $639,065 in total. In comparison, throughout the six years, elite lenders bid on average $41,232 per month for friends' projects (standard deviation $95,121). The fraction of elite who are also friends with some of the borrowers is 2.5 in June 2010, which is well above the fraction of 0.002 (±0.005) in a typical month.

Altogether, the market share of the elite is disproportionately large and limits contributions from friends. How does this compare to our initial finding about the friend first bidder? To address this question, we repeat the analysis shown in Figure 1A–B, except now we look at the first bid that comes from an elite lender instead of the very first bid. Specifically, we re-compute both the percentage of time elapsed before the first bid is placed and the percentage of the requested amount that this bid represents. Differentiating again between the project proposals that receive the first bid from a friend and those that do not, we obtain the numbers summarized in Table 1.

TABLE I. INVOLVEMENT OF THE ELITE IN TERMS OF TIME-TO-BID AND FUNDS RAISED WHEN FRIENDSHIPS ARE PRESENT/ABSENT

	P(Time taken<10%)	**P(Funds raised>10%)**
Friend first bidder	0.77 (0.71)[a.]	0.43 (0.17)
Not friend first bidder	0.57 (0.6)	0.07 (0.03)

[a.] For comparison, in brackets we show the probabilities computed for the very first bidders (cf. Figure 1A–B).

Accordingly, we observe that:

a) The probability that the time-to-bid for the elite lender is below 10% of the total running time of the proposal increases to 77% (from 71% for the first bidder) in the case of a friend, and decreases to 57% (from 60%) conversely. In other words, a friend first bidder accelerates the bid coming from the elite, while a not friend first bidder seems to even decelerate it.

b) The capital raised by the first bid that comes from the elite increases regardless of the source of the very first bid. In case of friends, the probability that the amount lent represents more than 10% of the target amount increases by 2.5 times: from 17% to 43%, which provides a considerable advantage to the loan request.

These results strengthen the finding that friend first bidders positively influence the progression of the bid. Their effect is visible even at the level of the elite. In the case of the latter, the discrepancy between friend and not friend bidders becomes yet more extreme: in terms of the time-to-bid the difference between proposals having friend vs not friend first bidders increases in the favor of the friend-supported loan; while with respect to the raised capital, a friend first bidder increases the investment of the elite dramatically. Thus, in the context of crowdfunding on Prosper, such minor local effects represented by network relations appear to trigger global phenomena.

IV. Conclusions and Discussions

One of the most important biases in crowdfunding is due to herding behavior [13]. The effects of this bias can be amplified considerably by the activity of the friends studied in this article. With this focus, we set out to investigate empirically the network effects arising in crowdfunding based on the example of Prosper, which is one of the largest peer-to-peer lending platforms in the U.S. Our analysis indicates that network ties react at the beginning *quicker* and throughout more *favorably* to loan proposals (by lending larger proportions of the requested amount), and are even able to mobilize further friends throughout the bidding process. The friendship network shows unique star-shaped structural signatures centered predominantly on borrowers. Such friendships lead to lasting “alliances” between borrowers and lenders, as well as an increased reciprocity in terms of returned favors. The diverse effects of friends also incorporate long-term co-lending, which is an implicit measure of the collaboration between lender pairs. Finally, in the broader context of the emerging crowdfunding market, friends reflect larger financial trends in consolidating power to an elite few.

Friendships, and implicitly network effects, are at the core of scientific inquiry in the financial setting because of their easy adaptation, lowered risk through social control, and reduced information asymmetry, which was identified to be the biggest challenge inherent to every lending setting [27]. The prevailing view is that friendships may be beneficial to all involved parties (borrowers, lenders, and the entire platform as a system). However, by systematically favoring the loan-requests of referent-others, such ties are potentially circumventing beneficial features of the lending system. Crowdfunding is popular because it bypasses the traditional banking risk mitigation channels such as collaterals and market research, for instance. The in-built governing mechanism behind the disintermediation between investor and entrepreneur is the *wisdom of the crowds* [28]. Scores of strangers objectively evaluating the merit of a loan request can increase the fidelity of the system by uncovering bad investments even in the absence of respected experts and a conventional financial institution. However, when friends band together in quickly starting the bidding process (therefore indicating that the project is meritorious), and by funding greater portions of the loan (thereby suggesting low risk), these ties can potentially “poison the well” by biasing other unsuspecting lenders towards favorably judging the loan when it may not necessarily merit it. This fear can be allayed by future investigations into the failure rates of such “friendly-startups”.

Similarly, it is possible for systemic malfeasance: by tacit assurance of reciprocity, friends can unload their underperforming debts to their connected others for temporary safekeeping as the auditing periods approach. Given two facts: the entry of large banks into the peer-to-peer lending markets, and their relatively frequent accounting malpractices, such fears are not unwarranted, and may continue without the benefit of objective public scrutiny. This too can be investigated in the future by studying the performance of elite funded loans.

In summary, the instance of the “socialization of finance” [2] investigated in this paper results in new business models which empower human ties and networks in ways unseen before. Our study uncovers remarkable possibilities for democratization, but also potential dangers. It remains to see how the wisdom of the crowds performs in the setting of crowdfunding, especially because the development of the latter depends on our ability to manage the arising new types of networks and the pace of collective learning in a strongly decentralized system.

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