With a Little Help from Friends: Strategic Financing and the Crowd

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Abstract

Based on a crowdfunding platform and social media account login data, we study the information role of financing from connected individuals (e.g., family and friends) of entrepreneurs. While financing from connected individuals is generally considered as a signal of high-quality projects, our results suggest that this might be a signal of funding performance manipulation. Entrepreneurs with moderate early funding performance strategically solicit investments from friends to encourage naïve investors to herd. Sophisticated investors discern manipulation and are less likely to invest. Manipulation exists even when sophisticated investors have significant market power and projects with manipulation deliver poorer funding performance.

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It is well recognized that entrepreneurs face frictions in financing from traditional sources, and in order to bridge the financing gap, they finance from informal sources, especially from family and friends (or, more broadly, investors socially connected to the entrepreneur, referred to as “friends” hereafter). While financing from friends is important and prevalent in the early stages of financing, its information role vis-à-vis external investors remains unclear. Some theories suggest that financing from friends signals good project quality because friends may possess favorable inside information (Leland and Pyle 1977); others, however, argue that financing from friends represents funding of last resort, and thus signals poor project quality (Lee and Persson 2016).[1] It is also conceivable that contributions from friends are neither strategic, nor do they contain any information about project quality, to the extent that friends have a strong incentive to help and contribute regardless of project quality.

There are several empirical challenges to identifying the information role of financing from friends and how it influences external investors' investment decisions and eventual financing success. First, the funding terms (e.g., equity and debt, debt seniorities, collateral requirements) and payoff structures are usually different for friends and external investors, and therefore it is challenging to disentangle the information role of friends' financing from payoff externalities. Second, investment timing is often very different for friends and external investors, and therefore their information sets can be significantly different. It is possible that project fundamentals may have changed dramatically when external investors invest in later stages of the project, and therefore it is difficult to disentangle the influence of friends' financing from the influence of updated project fundamentals on external investors' investment. Most importantly, investors are anonymous in many financing scenarios and researchers cannot identify which investors are connected to the entrepreneur.

Our paper empirically examines the information role of financing from friends by studying entrepreneurs' financing and investors' contributions on a reward-based crowdfunding platform. Crowdfunding has emerged as a major source of entrepreneurial finance in recent years. It had surpassed the market size for angel investors by 2015 and is rapidly approaching the levels of

[1] There are many potential reasons why financing from family and friends would be costly. In Lee and Persson (2016), financing from family and friends is costly because it jeopardizes an important source of insurance and undermines limited liability. In our context, financing from family and friends is costly because sophisticated external investors view it as a negative signal.

venture capital-backed finance. Crowdfunding had raised 34.4 billion USD globally by early 2017, and it is estimated that it will reach 93 billion in 2025.[2]

The process of entrepreneur financing on a reward-based crowdfunding platform generally proceeds as follows: an entrepreneur initiates a new funding campaign for her project on the platform, where she presents project-related information to the public, including project description, funding goal, funding duration, a number of contribution options (e.g., \$10, \$100) predetermined by the entrepreneur, and rewards (usually the product itself) associated with each contribution option. The crowdfunding platform also publicizes in real-time information about the progress of the fundraising campaign (e.g., the amount of money raised and the number of investors who have contributed to the project to date). In addition, most crowdfunding platforms have an "all or nothing" policy (AoN hereafter), i.e., entrepreneurs only get funding when their funding goals are met within the fundraising period, otherwise all the funds raised are returned to investors.

The reward-based crowdfunding platform provides an ideal setting to identify the information role of financing from friends. First, the funding terms and payoff structures are the same for friends and external investors. In reward-based crowdfunding platforms, the promised rewards associated with investments are predetermined and publicized on the platform. The predetermined contribution levels also avoid issues of pricing dynamics, which may involve complicated strategic issues. Second, the investment timing is roughly the same for friends and external investors because a crowdfunding fundraising campaign typically only lasts four to six weeks. Therefore, changes in project fundamentals are likely to be less important for the decisions of late investors. Third, the specific crowdfunding platform we analyze gives us access to the entrepreneurs' and investors' online social networks, and therefore we can identify whether an investor is an entrepreneur's online friend. Fourth, the platform publicizes the full detailed contribution history for each project, i.e., who contributed how much money at what time, and thus we are able to identify strategic financing by examining intra-day contribution patterns, especially at the beginning and end of the funding period. Finally, the AoN feature of crowdfunding platforms presents a clear threshold goal for entrepreneurs to strategically allocate investments from friends,

[2] World Bank report, Crowdfunding's Potential for the Developing World, 2013.

which allows us to detect strategic financing at some critical points in time during the fundraising process.

One concern about studying crowdfunding is the generalizability of our results to other financing settings, because most investors on crowdfunding platforms invest relatively small amounts of money and may not pay too much attention to the project. However, many studies have shown that the "wisdom of the crowd" plays a role similar to that of informed investors in financial markets, and crowdfunding may therefore help us understand how financial markets work in general. For example, studies show that the crowd delivers accurate estimates of firms' future earnings, even comparable to the Wall Street consensus (Adebambo and Bliss 2015; Da and Huang 2019; Jame et al. 2016). Researches have also shown that individual investors' judgement of a crowdfunding project's quality is similar to that of venture capitalists (Mollick 2013) as well as that of experts (Li 2015; Mollick and Nanda 2016). Finally, the fundraising outcomes on crowdfunding platforms can predict subsequent funding from venture capital experts and angel investors (Viotto da Cruz 2018; Xu 2018).

We collect data from DemoHour, one of the earliest crowdfunding platforms in China. Our data have all the details of investment history of every crowdfunding project, including investor ID, contribution amount, and timing. This information is public to all investors and researchers. More interestingly, DemoHour allows entrepreneurs and investors to sign up with their social network accounts (i.e., Weibo.com, China's "Twitter"). As online social networks on Weibo.com are public information, we are able to identify online friendships between entrepreneurs and investors through their Weibo accounts on DemoHour. One concern with the Weibo friendship construct is that the data are ex post, i.e., only collected after the fundraising campaign ended. We address this concern by validating the online friendship with a comparison of friends' vs. nonfriends' behavioral traits, including online interactions via Weibo prior to the start of the campaign. All validations show that these Weibo friends of the entrepreneur are likely to be socially connected to the entrepreneur even prior to the fundraising campaign. We discuss these validations in detail later in the paper.

Our main results are as follows. The first set of results examines whether friends make early contributions based on their inside information. We find that early contributions from friends are negatively correlated with the funding outcome (defined as the ratio of total amount of funds raised to the funding goal), the likelihood of "success" (defined as having met the funding goal) and the number of investors (controlling for the funding goal, the funding duration, and the number and amount of funding on the first day).[3] This negative association rules out the possibility that friends possess superior information about project quality compared with external investors.[4] This is so because if they had private information that the project quality is good, they would contribute early to convey a positive signal to external investors, which in turn would encourage their participation and increase the chance of fundraising success (Liu 2018). In that case, we would see a positive correlation between early contribution from friends and project fundraising success. However, we find the opposite. We interpret this as possible evidence of friends making early contributions to support the entrepreneur when early signs of fundraising success are not favorable.

Friends can support the entrepreneur for voluntary or nonstrategic reasons (e.g., they may want to help the entrepreneur for altruistic reasons), or to enable the entrepreneur to strategically manipulate potential external investors.[5] In order to rule out the possibility of voluntary support, we examine the time pattern of friends' contributions. We find that on the project launch day, friends' contributions decrease from daytime to nighttime for good quality projects, but in contrast, friends' contributions increase from daytime to nighttime for the moderate quality projects.[6] These contribution time patterns suggest that while entrepreneurs of good projects may receive favorable early signals about their projects and therefore do not need to call in friends to boost the first day fundraising outcome, entrepreneurs of moderate quality projects may receive worse signals. Facing more uncertainty about their projects being able to reach the funding goal, they may therefore start calling on friends late at night on the first day to boost the first day fundraising outcome. The contribution time patterns we find thus rule out the possibility that friends voluntarily contribute to entrepreneurs' projects because otherwise friends' contributions at nighttime should illustrate the same pattern across all projects.

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[3] As a validation exercise, we run similar regressions based on Kickstarter data and find similar results.
[4] Given the information role of financing from friends as the focus of our research, we use funding performance to measure project quality. The funding performance can be viewed as the market's ex ante subjective belief of project quality. Extant literature has shown that ex ante funding performance is highly correlated with measures of ex post project quality, such as reward delivery and later rounds of financing (Mollick 2015; Xu 2018).
[5] We do not differentiate whether it is the entrepreneur or friends who choose the timing of financing from friends.
[6] We classify projects as "Good" if their realized funding outcomes are significantly above the funding goal, and as "Moderate" if their realized funding outcomes narrowly pass the funding goal. "Bad" projects have too few contributions to identify any pattern with statistical power.

In addition to the contribution time patterns in the first day, we also examine friends' contribution pattern two days before the deadline of crowdfunding campaigns. The AoN feature of crowdfunding platforms presents a clear threshold goal for entrepreneurs to strategically allocate investments from friends at critical time points. We compare friends' contributions for successful projects (i.e., projects which had already reached their funding goals two days before the end of the campaigns) with the "almost successful" projects (i.e., projects which have raised more than 50% but less than 100% of their funding goals two days before the end of the campaign). We find that the "almost successful" projects receive a much higher ratio of contributions from friends than the successful projects in the last two days, suggesting that entrepreneurs of the "almost successful" projects ask for funding support from their friends to reach the funding goal threshold.

As our results provide evidence of strategic financing, a natural question is which types of investors will be attracted by entrepreneurs' strategic manipulation of financing from friends. We propose that there are two groups of investors in the crowdfunding market: sophisticated investors who can recognize when early contributions are manipulated and avoid investing in such projects, and naïve investors who cannot discern strategic financing and herd with the crowd.[7] Entrepreneurs of poor quality projects have to rely on manipulation and herding by naïve investors for funding success. However, such manipulation can only attract the naïve investors, and manipulated projects are less successful because sophisticated investors view financing from friends as an unfavorable signal and stay away.

We find evidence in support of our hypothesis. Based on the average fundraising outcomes of the projects they invest in, frequent investors are classified into two groups, sophisticated investors versus naïve investors.[8] We find that if a project has a high percentage of large contributions on the first day, it attracts fewer sophisticated investors but more naïve investors after the first day, suggesting that sophisticated investors may identify the strategic financing in the first day and avoid those projects, while naïve investors do not. In addition, we also find that

7 Sophisticated investors could either detect strategic financing from the pattern of contributions or might be able to independently evaluate project quality.

[8] We focus on the investors who have made more than one investment on this crowdfunding platform. We rank those investors based on the average fundraising outcomes of the projects (defined as the ratio of total amount raised to the funding goal) they support. Those in the top 20% in terms of performance are grouped as sophisticated investors and those in the bottom 20% are grouped as naïve investors.

sophisticated and naïve investors have different investment behavior.[9] Sophisticated investors invest almost three times as much per project as do the naïve investors, and they tend to wait and make investments at a later stage than do the naïve investors, which suggests that sophisticated investors are more rational and are willing to wait and learn.

Our paper makes a number of contributions to the literature on informal finance from friends and family. First, it is one of the few papers that directly examines the information role of financing from friends and how that interplays with financing from the crowd. We are able to do this because the platform we study allows us to obtain an arguably better measure of friends of entrepreneurs than that in other studies. For example, Kuppuswamy and Bayus (2018) infer family ties from investors' usernames—investors who share same last names with the entrepreneur are assumed to be family members. However, this measure by construction only potentially captures family, not friends who might be more important in crowdfunding platforms. Agrawal, Catalini, and Goldfarb (2014) infer friends from investors' behavioral traits on the crowdfunding website and a select sample of entrepreneurs who explicitly identify friends and family members. Deb, Oery, and Williams (2019) recognize that many investors in Kickstarter are "donors" rather than buyers. Arguing that donors contribute not for receiving the consumers' surplus from the product but because they get a fixed nonpecuniary payoff from the success of the project (somewhat similar to family and friends), they derive a number of implications for donor behavior in a dynamic contribution game and find support in the data.[10] As the identification of family and friends is not strong in these studies, they cannot address the issue of strategic financing via contributions from family and friends.

Our research also contributes to the entrepreneurial finance literature, and, in particular, to the crowdfunding literature. This literature has tended to conclude that the information advantage of family and friends, and their participation in financing, has positive implications for project financing success. Informal finance in the form of financing from family and friends is supposed

[9] We also ranked investors based on the fundraising outcomes of the first projects they invest in and examined the fundraising outcomes of the projects they subsequently invest in. Investors ranked in the top 20% on the basis of the performance of the first projects they invest in have better fundraising outcomes as well as lower percentage of first day contributions for the subsequent projects they invest in than those ranked in the bottom 20%.

[10] One particular implication that is consistent with our findings is that donors tend to contribute either early or late in the campaign, whereas buyers participate early. However, while the authors do introduce learning in a version of the model, all investors are sophisticated.

to have lower information and monitoring costs (Stiglitz 1990, among many others) and to mitigate moral hazard through the threat of social sanctions or other nonpecuniary costs of default (Besley, Coate, and Loury 1993).[11] In crowdfunding, Kuppuswamy and Bayus (2018) mention that there is a "… general belief among crowdfunding pundits who argue that successful projects create a critical mass of early funding from the people in their close social circles (de Witt 2012; Steinberg 2012)." [12] However, our results suggest that the small contributions that are typical on crowdfunding platforms and the AoN feature might create perverse incentives for entrepreneurs to seek financing from family and friends, not simply as an additional source of funding, but to generate (uninformed) herding. Our research finds that such strategic financing can lead to poor fundraising outcomes for entrepreneurs' crowdfunding campaigns. In other words, a project's early success can be a weaker signal of its continued success, and this may prevent new investors from contributing if the opportunity costs of participation are high (Deb, Oery, and Williams 2019).

Finally, while a vast majority of studies on crowdfunding conclude that crowdfunding campaigns as well as other online platforms typically capitalize on informed herding, our results find that, as implied by entrepreneurs' strategic financing from friends, not all early investors invest on the basis of information. [13] Sophisticated investors either detect strategic financing from the patterns of early contributions, or use their own information about projects, to stay away from bad quality projects. Thus, there is still wisdom in the crowd, to the extent that projects with strategic financing are associated with poorer fundraising outcomes. On the other hand, strategic financing does induce naïve investors to participate, i.e., they herd when they see large amounts of early contributions.

The rest of the paper is organized as follows. We discuss the empirical strategy to identify the information role of friends and strategic financing in Section I. We present our financing settings and data in Section II, and discuss our results in Section III. We conclude in Section IV.

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[11] However, as noted above, this view is questioned by Lee and Persson (2016).

[12] Agrawal, Catalini and Goldfarb (2014) state "The entrepreneurial finance literature makes frequent reference to the role of friends and family (F&F) as an important source of capital for early-stage ventures. Researchers have emphasized F&F's informational advantages concerning the quality of the entrepreneur (Cumming and Johan 2009)." They also note that "Despite the acknowledged importance of F&F, few empirical studies focus on this form of investment, likely owing to a paucity of data."

[13] See Zhang and Liu (2012) for evidence from the microloan market. Liu (2018) and Astebro et al. (2019) provide theoretical models and empirical evidence of informed participation, while Xu (2018) and Viotto da Cruz (2018) provide evidence on the feedback value of crowd investment.

I. Competing Hypotheses and Empirical Strategy

There are several alternative hypotheses regarding the role that contributions from individuals connected to the entrepreneurs (henceforth, “insiders” or “friends”) could play on a crowdfunding platform. We now discuss these in turn and outline how we design tests to distinguish between alternative mechanisms.

Strategic Insider Financing Hypothesis (SIH): According to this hypothesis, friends—potentially at the behest of the entrepreneur—strategically time their contributions to manipulate funding performance. There are two groups of investors in the market: while sophisticated investors may be able to infer the manipulation (or base their decisions on their own signals), naïve investors cannot discern manipulation and exhibit herding behavior. As a result, entrepreneurs with poor early funding performance may call on friends to contribute, with the objective of boosting funding performance and drawing in naïve investors. However, if the early funding performance is good, then the entrepreneur has no incentive to manipulate.

Informed Insiders Hypothesis (IIH): This hypothesis maintains that friends have inside information about project quality. If they perceive favorable signals about the project, they would make large and early contributions to motivate other investors in order to make sure the project meets the AoN target (Liu 2018). Both naïve and sophisticated investors would invest following larger early contributions by family and friends.

Nonstrategic Insider Financing Hypothesis (NIH): This maintains that friends just want to contribute to show their support. They do not time or change the amount of their contribution based on the total contribution amount. Their actions are not informative about the quality of projects.

Indifferent Investor Hypothesis (INH): Under this hypothesis, friends do not possess superior information compared to outside investors. Their contributions are as informative as others’ contributions.

No Learning Hypothesis (NLH): Products are completely private value goods and investors do not learn from others’ actions. The contribution history shows the distribution of private value.

Under *SIH*, *IIH*, and possibly *NIH*, family and friends would be contributing early. However, a key distinguishing implication between *SIH* and *NIH* on the one hand and *IIH* on the other hand is the relationship between early contribution by friends and eventual funding outcome. Under *IIH*, early contributions by friends are a good signal and will attract both naïve and sophisticated investors alike, leading to a positive relationship between early contributions by friends and eventual project funding success. In contrast, under *NIH*, friends' early contributions are based not on information, but on altruism. Thus, if good quality projects attract more early external support from informed investors, a mechanical negative association between the importance of early contributions by friends (relative to all contributions) and eventual project funding success can result. *SIH* also predicts a negative relationship. According to *SIH*, entrepreneurs with poor quality projects and negative early signals have stronger incentives to solicit contributions from friends to make the project look appealing to naïve investors. However, to the extent that sophisticated investors stay away from bad quality projects, these projects are less likely to succeed. *SIH* therefore implies a negative relationship between the importance of early contribution from friends and eventual project funding success. The one caveat here is that if the early signals are extremely bad, the manipulation incentives can also diminish. In this case, both the very good and very bad projects could have lower contributions from friends in relation to all other contributions, and the association between contribution from friends and eventual fundraising success could weaken. However, if a core amount of support from friends still remains for these extremely poor quality projects (similar to *NIH*), even when there is no active manipulation for such extremely low quality projects, a negative relationship between the contribution from friends and eventual funding success will be observed for the overall sample across all types of projects.

Clearly, both *INH* and *NLH* imply no association between early financing from friends and subsequent project funding success. [14] This leads to the first of our testable empirical implications:

Empirical Implication I (SIH and NIH vs. Other hypotheses): Early contributions from friends will be negatively associated with eventual project funding success.

In order to test Empirical Implication I, we focus on large contributions on Day 1 of a project's launch, which are likely to come from insiders, as we discussed later. We investigate how large contributions on Day 1 are related to the final fundraising outcome of a crowdfunding project.

[14] For the No Learning Hypothesis (NLH), if contributions from friends are nonstrategic, then similar to the NIH case, early contributions from friends may be mechanically negatively related to eventual project funding outcome. However, as we show later, sophisticated investors typically wait and cluster their contribution timing at 14-20 days after the funding campaign starts, suggesting that sophisticated investors do want to wait and learn from others.

Next, we discuss how we further distinguish between *SIH* and *NIH* if the test of Empirical Implication I rejects the other hypotheses. In order to investigate whether entrepreneurs strategically time their friends' contributions, we focus on two critical time periods—Day 1 nighttime and the last two days before a project's fundraising deadline. The nighttime of the first day is crucial because (as we discuss further below) Day 1 contributions are an important determinant of eventual fundraising success. Thus, under *SIH*, if an entrepreneur sees that the Day 1 fundraising outcome is not progressing well, she is likely to call on friends towards the end of Day 1. Similarly, shortly before the fundraising deadline, under *SIH*, we would expect greater endeavor by entrepreneurs who still face uncertainty about reaching the goal, compared to those who have already reached the goal. For *NIH*, we should expect no such differences between insider investors' contribution patterns depending on project quality. This brings us to the second testable empirical implication:

Empirical Implication II (SIH vs. NIH): Contributions by friends would be greater than contributions from external investors in the nighttime of Day 1 and the last two days of the fundraising campaign for moderate quality projects than those for good quality projects.

To implement the tests of this empirical implication, we classify projects based on eventual funding success or the fraction of funding target reached with two days remaining.

Finally, to further validate the *SIH*, we test some additional empirical implications of *SIH*, some of which are unique to that hypothesis. In particular, under *SIH*, entrepreneurs choose to manipulate even though more insider financing is associated with poorer funding performance (Empirical Implication I). *SIH* posits that external investors are heterogeneous. Specifically, while strategic insider financing encourages more naïve investors to herd, there exists a group of sophisticated investors who do not herd because they either observe other signals about project quality or are aware of manipulation and consider early stage insider financing as an unfavorable signal. Therefore, *SIH* predicts different types of behavior for sophisticated and naïve investors. First, in terms of contribution timing, sophisticated investors are expected to invest later than naïve investors because sophisticated investors would wait and learn the quality of a project by observing a project's contributions from insiders or evaluation of their own signals. Second, compared with naïve investors, sophisticated investors would be less likely to invest when the first day contribution by friends is high in relation to all contributions.

Empirical Implication III (SIH): (i) Sophisticated investors will invest later than naïve investors in projects. (ii) When insider financing is higher, sophisticated (naïve) investors will be less (more) likely to invest in the project when the first day contribution by friends is high in relation to all contributions.

To implement this test, we classify investors as sophisticated or naïve based on the average fundraising outcomes rate across all the projects they invest in. And we investigate the investing behavior of those two groups of investors.

II. Data

A. Sources

Our data come from DemoHour, which was one of the largest reward-based crowdfunding platforms in China during our data collection period. The setting of DemoHour (Appendix A) is similar to other reward-based crowdfunding platforms such as Kickstarter. DemoHour also has the AoN policy, i.e., entrepreneurs only get funding when their funding goals are met within the fundraising period; otherwise all the funds raised are returned to investors.

We collected data for 896 crowdfunding projects on DemoHour that were launched and concluded between July 31, 2011 and August 30, 2014. For each project, we collected the project-related information such as funding goal, funding duration, and industry (e.g., art, charity, design, music, and technology; see Appendix B). We also obtained the full detailed investment history, i.e., who (investors' usernames) invested how much money to what project at what time. Our dataset comprises 821 entrepreneurs who initiated 896 crowdfunding projects, and 68,015 investors who made 116,104 contributions (see Table 1 for descriptive statistics). An average campaign had a funding goal of RMB 20,995, lasted for 43 days, and attracted 116 investors who each invested RMB 248 on average. About 56% of the projects achieved their funding goal, with an average of RMB 32,687 raised per project. The average fundraising outcome—the total amount of money raised divided by the funding goal—of a crowdfunding project is 4.76. Similar to Kickstarter (Mollick 2014) the distribution of the fundraising outcomes is a U-shaped curve (Figure 1), that is, most projects achieved either less than 50% of the funding goal or more than 100% of the funding goal.

Importantly for our purposes, DemoHour allows people to sign up with their online social network accounts (Weibo, China's Twitter), and Weibo's data is public information. In our data, 669 entrepreneurs and 32,560 investors used their Weibo accounts to sign up to DemoHour. We access their Weibo accounts and collect the list of their Weibo friends.

B. Identifying Friends

We propose two measures of friends for our analysis, one based on the Weibo data and one based on large Day 1 investments. We argue that depending on the context, one is more useful than the other.

The first measure is based on the Weibo online social network data: we define an entrepreneur and an investor as friends if they follow each other on Weibo. In our sample, 11,726 investors are identified as friends of 504 entrepreneurs. Based on this definition, we find that friends invest more money than external investors (see the results of a regression on Table 2). One concern is that investors who sign up via social media accounts are different from investors who sign up via crowdfunding accounts and therefore their investment behaviors are not comparable. To address this issue, we specifically examine 778 investors who invest in more than one project and who invest as a friend in some projects but as an external investor in other projects. We find that an investor invests significantly more money (RMB 304) as a friend of the entrepreneur than she does as an external investor (RMB 155).

There are two potential concerns associated with this definition. First, the choice of signing up with a Weibo account can potentially be endogenous. People who try to manipulate funding performance (e.g., friends, PR firm hired by the entrepreneur, or entrepreneurs themselves) are likely not to sign up with a Weibo account because they want to hide their identities; instead they would sign up with anonymous accounts and be identified as an external investor according to our Weibo friend definition. However, this endogeneity issue suggests that we are likely to underestimate the strategic financing behavior.

Second, the Weibo online social network data are ex post, i.e., we collected the Weibo data after the funding campaign finished. Therefore, the Weibo friendship may be established after an investor makes investment in an entrepreneur's project. For example, entrepreneurs may follow ex post investors who made a large investment on Weibo, and likewise, these investors may follow entrepreneurs because they like the projects. To address this issue, we manually collected the whole history of Weibo interactions among a randomized subsample of entrepreneurs and investors. We find that among 620 pairs of friends, 58.06% have interactions (with each other, or making comments on each other's posts) before the campaign was launched on DemoHour.[15] As a benchmark, only 0.81% of 743 randomly matched investors and entrepreneurs have interactions. Therefore, the interaction data suggest that friendships identified based on our ex post measure are likely to exist ex ante as well. Furthermore, we validate the ex ante friendship by examining the crowdfunding platform account registration time. Similar to the behavioral traits in Agrawal, Catalini, and Goldfarb (2014), compared with external investors, entrepreneurs' friends should be more likely to sign up on the crowdfunding platform on the launch day of entrepreneurs' projects, in order to support their friends' projects. Table 3 shows that in our data 15.48% of Weibo friends signed up on the crowdfunding platform on the launch day of entrepreneurs' projects, significantly higher than 7.74% among external investors. This contrast becomes larger when we examine the percentage of friends (43.11%) vs. external investors (25.81%) signing up within one week after the launch day of entrepreneurs' projects. Taken together, all validations show that our Weibo friendships are likely to exist prior to the fundraising campaigns.

The motivation for our second measure of friends' contributions is as follows. While Weibo friends help researchers identify strategic financing, it is unlikely that investors would go through Weibo accounts one by one and check whether an investor is a Weibo friend of the entrepreneur. Instead, as individual investors' investments are public information, an investor may infer friendship between an entrepreneur and other investors from the amount of money other investors invest in the project, especially at the early stage of a crowdfunding campaign (e.g., Day 1) when all investors are likely to be cautious about making large investments while significant uncertainties remain.

[15] This estimate is likely to be the lower bound because we miss connections for those who are not active on Weibo, or hide their past interaction history, or changed the account names later so we are not able to map their accounts to early activities.

We validate this intuition by investigating the relationship between large investments made on Day 1 and Weibo friends. An investment to a campaign is defined as "large" if the amount is above the campaign's average contribution amount. We run a Probit regression where the dependent variable is a binary variable indicating whether an investor is a Weibo friend. The results show that it is positively related with *LargeInvestment*, a dummy variable indicating whether this Day 1 investment is a large amount, suggesting that large Day 1 investments are likely to be from Weibo friends (Table 4). Based on this validation, we define friends from investors' perspective based on the large investments on Day 1.

Compared with the definition of friends based on Weibo, the definition of friends based on a large Day 1 investment may miss friends who invest small amounts on Day 1. However, it captures friends that cannot be identified from Weibo, e.g., Day 1 investments that are made by the entrepreneurs (via different accounts), PR firms, and friends who choose not to sign up via Weibo accounts.

C. Day 1 Funding Performances and Final Fundraising Outcomes

Our analyses focus on Day 1 of a crowdfunding project because many anecdotes as well as our data suggest that the fundraising performance on Day 1 is crucial for the final fundraising outcomes. Our data shows that the average project raised RMB 4,581 on Day 1, which accounts for 15.59% of the total amount raised. We further verify the importance of Day 1 by regressing the total amount of money raised in a project (log-transformed), $Log(TotalAmount)$, on the amount of money raised on Day 1 (log-transformed), $Log(FirstAmount)$, while controlling for the number of investors on Day 1 (log-transformed), $Log(FirstInvestor)$, fundraising campaign duration, *Duration*, and the fundraising goal (log-transformed), $Log(Goal)$. We also control for fixed effects for project industries (ρ_j include dummies for *Art, Book, Charity, Design, Music, Tech, and Video*) and fixed effects for time effect (dummies for day of the week of Day 1, i.e., Monday to Saturday). The model is specified as follows:

$$(1)\quad Log(TotalAmount_j) = \alpha + \beta_1 \log(FirstAmount_j) + \beta_2 \log(FirstInvestor_j) + \beta_3 Duration_j + \beta_4 \log(Goal_j) + \rho_j + \varepsilon_j$$

Column 1 in Table 5 reports the regression results. We obtain a positive and significant coefficient for $\log(FirstAmount)$, suggesting that the investment on Day 1 is positively related to the total amount of money raised. We also use a Probit regression with a binary dependent variable indicating whether a project achieved its funding goal (1 if yes and 0 otherwise) in Column 2. We again obtain a positive and significant coefficient for $log(FirstAmount)$, suggesting that the investment on Day 1 is positively related to the probability of achieving the funding goal. The high R^2 also suggests that the Day 1 investment is highly correlated with final fundraising outcomes. Taken together, these results show that Day 1 investment is indeed crucial for the final fundraising outcome and therefore we focus on Day 1 to investigate the entrepreneur's strategic financing.

III. Results

A. Friends' Investments on Day 1 and Final Fundraising Outcomes

First, we test whether friends' investments on Day 1 contain positive, negative, or no information about a crowdfunding project (Empirical Implication I in Section I). Recall that from the external investors' perspective, the ratio of the number of large contributions on Day 1 to total number of contributions indicates the extent of participation by friends. If friends have superior (positive) information and make large and early contributions, a higher ratio of Day 1 large contribution predicts a better final fundraising outcome, since informed herding will follow (Informed Investor Hypothesis, *IIH*). In contrast, if early signals about project quality are negative, the entrepreneur would call on friends to boost Day 1 performance, and induce uninformed herding by naïve investors. However, if sophisticated investors detect manipulation or observe project quality and do not invest, a higher ratio of Day 1 large contributions would predict a worse fundraising outcome (Strategic Insider Financing Hypothesis, *SIH*). Alternatively, if friends contribute in Day 1 simply because they want the project to succeed (altruism), and good projects attract more external investment, then since the large Day 1 contribution by friends is exogenous to project quality, we could mechanically get a negative association between the large Day 1 contribution ratio and a successful fundraising outcome (Nonstrategic Insider Financing Hypothesis, *NIH*). Finally, friends might have no information advantage over outsiders and could be indifferent to fundraising success or failure (Indifferent Investor Hypothesis, *INH*), or products are completely private value goods and investors do not learn from others' actions (No Learning Hypothesis, *NLH*), in which cases we would expect no association between large Day 1 contributions and fundraising success.

To implement the test of Empirical Implication I, we calculate the ratio of large investments on Day 1 of project j's launch ($LargePer_j$), that is,

$$LargePer_j = \frac{the\ number\ of\ large\ Day\ 1\ investments\ in\ project\ j}{the\ total\ number\ of\ Day\ 1\ investments\ in\ project\ j}$$

Then we regress the final fundraising outcomes of campaign j on $LargePer_j$. The first final fundraising outcome is the total amount of money raised in a project ($TotalAmount$; log-transformed because of its highly skewed distribution: skewness = 9.83, $p < .01$; Kurtosis = 115.36, $p < .01$). As shown in equation (2), other than our focal variable $LargePer_j$, we control for log-transformed funding goal (*Goal*), funding duration (*Duration*), log-transformed amount of money raised on Day 1 (*FirstAmount*), log-transformed number of investors on Day 1 (*FirstInvestor*), fixed effects for project industry, and fixed effects for project launch day.

(2) $$Log(TotalAmount_j) = \alpha + \beta LargePer_j + \gamma_1 \log(Goal_j) + \gamma_2 Duration_j + \\ + \delta_1 \log(FirstAmout_j) + \delta_2 \log(FirstInvestor_j) + \rho_j + \varepsilon_j$$

Table 6 reports the regression results. In column 1 we obtain a negative and significant coefficient for $LargePer$, suggesting that a large percentage of large Day 1 investments is associated with less money raised. The estimate implies that a standard deviation increase in the large Day 1 investment ratio corresponds to a 54.9% decrease in the total amount of money raised. The estimates presented in columns 2 and 3 of Table 6 use alternative fundraising outcomes as dependent variables: the total number of investors in column 2 (log-transformed because of its highly skewed distribution: skewness = 8.91, $p < .01$; Kurtosis = 100.26, $p < .01$) and a binary dependent variable indicating whether a project achieved its funding goal (1 if yes and 0 otherwise) in column 3. We again obtain negative and significant coefficients for $LargePer$ in both models, suggesting that a higher percentage of large Day 1 investments is associated with smaller total number of investors for the project, and a lower probability of achieving the funding goal. Taken together, the results of our analyses show the negative effect of large Day 1 investments on the final fundraising outcomes.[16]

[16] We also estimate the relationship between the large Day 1 investments from individuals who are Weibo friends of entrepreneurs and the final fundraising outcomes of crowdfunding campaigns. Consistent with the results in Table 6, we find that a higher percentage of large Day 1 investments from friends is associated with less money raised eventually.

One may wonder whether the negative relationship between large Day 1 investments and the final fundraising outcome comes from the endogeneity of potential investors. Investors with certain characteristics may be interested in certain types of projects. To address this issue, we study a panel of 12,378 individual investors who invested in more than one crowdfunding project and examine how they respond to the large Day 1 investments. With fixed effects to control for individual investors' unobserved heterogeneity, we are able to investigate whether an investor invests more money in a project with a higher percentage of large Day 1 investments than he does in a project with a lower percentage of large Day 1 investments.

In a panel data regression, the dependent variable is individual investor i's investment in project j at time t. In addition to our focal variable $LargePer$ and the control variables in equation (2), we control for the cumulative contribution amount before the day of investor i's investment, the investment amount on the day before his investment day, and the Weibo friendship between her and the entrepreneur. Most importantly, we include fixed effects for individual investors to control for unobserved investor heterogeneity.

The results of column 1 (Table 7) show a negative and significant coefficient of $LargePer$, suggesting that investors invest less money in projects that received a greater percentage of large Day 1 investments. As a robustness check, we replace $LargePer$ in column 1 with the percentage of large Day 1 investments from Weibo friends ($FriendLargePer$) in column 2. The dependent variable and control variables remain the same as in column 1. The results (Table 7) show that the coefficient of $FriendLargePer$ is also negative and significant, consistent with the results in column 1.

Another concern is that the negative relationship may be driven by the endogenously chosen funding goal. An entrepreneur with many supporting friends might be overconfident and might set an unrealistically high funding goal, resulting in a greater chance to fail. In order to rule out this alternative explanation, we examine the relationship between the funding goal and large Day 1 investments. If this alternative explanation is true, we should find the funding goal is positively related with the large Day 1 investments. However, we find that the relationship is negative and not significant (Table 8).

All the results suggest that large Day 1 investments are negatively and significantly associated with the final fundraising outcomes. This rules out the informed investor hypothesis

(*IIH*), indifferent investor hypothesis (*INH*), and no learning hypothesis (*NLH*). On the other hand, it is consistent with both the strategic insider financing hypothesis (*SIH*) and the nonstrategic insider financing hypothesis (*NIH*).

As a validation exercise, we also examine the relationship between large Day 1 investments and the final fundraising outcomes on one of the biggest crowdfunding platforms Kickstarter, and we find similar results, suggesting that the negative association between large Day 1 investments and the final fundraising is not unique to the crowdfunding platform we study.[17]

B. Timing Friends' Investments

Next, we present evidence in support of entrepreneurs' strategic insider financing hypothesis (*SIH*) that also rules out the nonstrategic insider financing hypothesis (*NIH*), as discussed under Empirical Implication II in Section I. We focus on two critical time windows—Day 1 and the last two days before a fundraising campaign concludes—when entrepreneurs have particularly strong incentives to strategically ask their friends to help with the success of their projects. Specifically, we investigate whether entrepreneurs' Weibo friends invest at critical time points (supporting the strategic insider financing hypothesis *SIH*) or simply invest at random time points (supporting the nonstrategic investment hypothesis *NIH*). We examine entrepreneurs' strategic financing, and we use the definition of friends from entrepreneurs' perspectives, i.e., Weibo friends.

i. Late Night Calls on Day 1

As discussed earlier, Day 1 is critical for the fundraising success of a crowdfunding project. Other factors held constant, a project raises more money in total if it raises more money on Day 1. Therefore, we propose that entrepreneurs carefully monitor the fundraising progress on Day 1; compared with entrepreneurs of good quality projects, entrepreneurs of moderate quality projects

[17] The Kickstarter data are from Etter, Grossglauser, and Thiran (2013). The data have basic project level information (project ID, funding goal, if a project reached its funding goal eventually, launch date, and fundraising duration) of 16,042 Kickstarter projects. The data also have 1000 uniformly-spaced samples of the fundraising status of each project, including the number of investors and amount of money raised at the time of data scraping. As Kickstarter does not provide public information of individual investors' investment amounts, we calculate the large Day 1 investments based on the project fundraising status.

are most uncertain about the fundraising outcomes, and thus are most likely to ask their friends to invest near the end of Day 1 if they observe that the fundraising performance during daytime is not good.[18] Therefore, if our hypothesis on entrepreneurs' strategic financing is true, for moderate quality projects we should see more friends investing at nighttime than that during daytime of Day 1. Such patterns are not expected for good quality projects because those projects are likely to succeed even without friends' investments.

In our test, we choose the projects that started between 9 am. and 13 pm. and examine the hourly investments from entrepreneurs' friends from daytime to nighttime of Day 1. As a project's quality is unobservable, we use the ex post fundraising outcomes to categorize projects into good and moderate quality projects. The projects that eventually raised no less than twice of their funding goals are grouped as good quality projects (92 projects), and the projects that raised 90% to 130% of their funding goals are grouped as moderate quality projects (87 projects).

We calculate the ratios of Weibo friends' investments (in terms of the number of contributions) in every three-hour segment from 9 am. to 23:59 pm. for these two groups of projects and then de-mean the ratios within each group of projects. We plot these ratios in Figure 2a. The figure shows that compared with the good quality projects, the moderate quality projects on average have a higher percentage of friends' investments. Most interestingly, the percentage of friends' investments in moderate quality projects increases during late night (between 21 pm. and 23:59 pm.). In contrast, the percentage of friends' investments in the good projects decrease during late night. Such patterns are confirmed when we do not de-mean the ratios (Figure 2b). Similarly, we calculate the percentage of money coming from entrepreneur's friends every three hours on Day 1 in each group of projects. We plot those ratios (de-meaned in Figure 3a and not de-meaned in Figure 3b). Both figures show similar patterns as in figures 3a and 3b.

More formally, to test whether friends invest differently in good vs. moderate quality projects from daytime to nighttime, we adopt the following regression specification:

[18] As there are too few friends' investments in bad projects (14 friends' investments in 90 bad projects) to make any statistical inference, we focus on the good and moderate quality projects.

(3) $FriendPer_{jt} = \alpha + \beta ModerateProjects_j + \sum_{t=1}^{4}(\theta_t Time_{jt} + \delta_t Time_{jt} * MediocreProjects_j) + \gamma_1 \log(Goal_j) + \gamma_2 Duration_j + +\delta_1 \log(FirstAmout_j) + \delta_2 \log(FirstInvestor_j) + \rho_j + \varepsilon_j$

We regress the percentage of friends' investments in every three-hour segment from 9 am. to 23:59 pm ($FriendPer$) on a dummy variable indicating whether a project is moderate or good ($ModerateProjects$ equals 1 if a project is moderate and 0 if the project is good). In order to test the robustness of good vs. moderate projects, we rank all projects by their fundraising outcomes (i.e., the ratio of the total amount of money raised to the funding goal), and group the projects based on quintiles. The projects in the highest quintile are grouped as good projects (114 projects with fundraising outcomes no less than 1.66), and the projects in the second highest quintile are grouped as moderate projects (110 projects with fundraising outcomes between 1.02 and 1.654). In order to test the trend of friends' investments from daytime to late night, we add time dummies ($Time$: four time dummies for the three-hour segments between 9 am. and 23:59 pm.) and the interactions between the time dummies and $ModerateProjects$. All control variables are the same as those in equation (2).

Table 9 reports the regression results. In column 1, the interactions between $ModerateProjects$ and the late night interval (21 pm. – 23:59 pm.) is positive and marginally significant, suggesting that compared with good projects, moderate projects have more friends' investments at late night than other time. To test the robustness of the results, we replace the percentage of investments (in terms of the number of contributions) from friends with the percentage of money from friends in column 2. Other variables are the same as those in column 1. We again obtain a positive and significant interaction between $ModerateProjects$ and the late night dummy, suggesting that compared with good projects, moderate projects have more money from entrepreneur's friends at late night than other time. Interestingly, in column 2 the interaction between $ModerateProjects$ and the early night time interval (18 pm. – 20:59 pm.) is also positive and significant, implying that the friends' investments in the moderate projects increase gradually from early night to late night.

Taken together, both the figures and regression results show evidence to support the entrepreneurs' strategic insider financing hypothesis (*SIH*). Entrepreneurs of moderate quality projects ask their friends to invest at nighttime when they observe the fundraising on the daytime is unsatisfactory. These results also rule out the nonstrategic insider financing hypothesis (*NIH*), which predicts no relationship between increasing friends' investment at late night and the project quality.

ii. Filling the Gaps When Fundraising Deadline Approaches

Another critical time point to identify entrepreneurs' strategic financing is when the fundraising deadline approaches. The AoN policy on crowdfunding platforms implies that the entrepreneurs need to reach their funding goals before the fundraising deadline; otherwise their fundraising campaigns fail and all investments return to investors. The AoN policy provides a well-defined incentive for entrepreneurs' strategic financing: when the fundraising deadline of a crowdfunding project approaches and the total amount of money raised is close to (but short of) the funding goal, the entrepreneur has strong incentives to ask help from friends in order to reach the funding goal.

We focus on the last two days before a crowdfunding campaign concludes. If strategic financing exists, we should expect that the projects that almost reach their funding goals have more friends' investment in the last two days than projects that either have already reached their funding goals or projects with contributions far below their funding goals. Following this logic, we categorize all crowdfunding projects into three groups based on how close the amount of money raised is to the funding goal at the beginning of the last two days: projects which have already reached their funding goals are grouped as "successful projects" (441 projects), and projects which have raised over 50% but less than 100% of the funding goals are grouped as "almost successful projects" (85 projects).[19]

We calculate the ratios of friends' investments (in terms of the number of contributions) in half-day segments for the last two days before the crowdfunding campaigns conclude and then de-mean those ratios within each group of projects. We plot those ratios in Figure 4a. The figure shows that "almost successful projects" have a higher percentage of friends' investments than the

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[19] The rest of the projects have raised no more than 50% of the funding goals. We group them as "far from successful projects" (370 projects). But as there are only 6 investments from friends among 370 projects in the last two days, it is difficult to make conclusions from the patterns. Therefore, we focus on the "successful projects" and "almost successful projects."

"successful projects" have. These patterns are also confirmed when we do not de-mean the ratios (Figure 4b). In addition, we examine the percentage of money coming from entrepreneur's friends in the last two days. The de-meaned ratios in Figure 5a and the ratios without de-meaning in Figure 5b show very similar patterns: "almost successful projects" have a higher percentage of friends' investments than the "successful projects." Therefore, figures 5a, 5b, 6a, and 6b suggest that entrepreneurs whose fundraising campaigns almost reach the funding goals two days before the deadlines are strategically asking help from their friends, supporting our strategic insider financing hypothesis (*SIH*).

To further test the robustness of entrepreneurs' strategic financing when the fundraising deadline approaches, we regress log-transformed friends' investments in the last two days[20] on a dummy variable, *AlmostSuccessfulProjects*, which equals 1 if it is an "almost successful project" and 0 if it is a "successful project." The control variables are very similar to those in equation (2) except that here we also add the log-transformed number of investments from nonfriends (or the log-transformed amount of money from nonfriends). In Table 10, a positive and significant coefficient of *AlmostSuccessfulProjects* in column 1 suggests that compared with "successful projects," "almost successful projects" have more friends' investments in the last two days, consistent with the patterns we observe in figures 5a, 5b, 6a, and 6b. The model results are robust when the dependent variable changes to the log-transformed amount of monetary contribution made by an entrepreneur's friends (column 2), when we do not take log transformation of the number of investments (column 3), and when we do not take log transformation of the amount of money (column 4).

Taken together, both the figures and regressions show evidence to support our strategic insider financing hypothesis (*SIH*) by showing that entrepreneurs of "almost successful projects" strategically ask their friends to invest in the last two days before the fundraising deadline so that their projects can reach the funding goals.

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[20] As friends' contributions in the last two days are very limited in both "successful projects" (26 friends' contributions in 441 projects) and the "almost successful projects" (6 friends' contributions in 370 projects), it is difficult to test in regressions the patterns using the percentage of friends' investments (or the percentages of friends' money). Instead, we use the log-transformed number of friends' investments in the last two days as the dependent variable and control for the log-transformed number of investments from nonfriends in Model 13. Similarly, in Model 14 we use the log-transformed amount of money from friends as the dependent variable and control for the log-transformed amount of money from nonfriends.

C. Sophisticated vs. Naïve Investors

We next address Empirical Implication III about what kind of investors will be attracted by entrepreneurs' strategic financing. We argue that investors in the crowdfunding market are heterogeneous. Specifically, there are two groups of investors: the "sophisticated" investors who can discern entrepreneurs' strategic financing, considering it as an unfavorable signal, and avoid such projects, and the "naïve" investors who cannot recognize strategic financing but herd with the crowd. In other words, strategic financing by the entrepreneurs can only attract the naïve investors.

We focus on the 12,378 investors who invested in more than one project. We rank them based on the average fundraising outcomes (i.e., the total amount of money raised divided by the funding goal) of the crowdfunding projects they supported. We group the top 20% of investors (2,478 investors) as "sophisticated investors" and the bottom 20% of investors (2,477 investors) as "naïve investors." Next, we examine whether these two groups invest differently.

First, we find that sophisticated investors invest significantly more money (RMB 1733.60) than naïve investors do (RMB 353.45, $p<0.001$), and sophisticated investors invest in significantly more projects (3.94) than naïve investors do (3.16, $p<0.001$). The distributions of investment amount from sophisticated and naïve investors confirm that larger contributions are more likely to come from sophisticated investors than from naïve investors (Figure 6). The distributions of investment time of sophisticated and naïve investors show that while naïve investors' investing time follows a more dispersed time distribution, sophisticated investors concentrate in the mid/late stages of the campaigns (Figure 7). These findings are consistent with the idea that the sophisticated investors assess and evaluate the projects before they "jump in", and once they decide to invest, they invest more.

Next we investigate whether the projects supported by sophisticated investors are different from the projects that naïve investors invested in, especially for the large investments on Day 1. We find that the projects supported by sophisticated investors have a significantly lower percentage of large investments on Day 1 (15.72%) than the projects naïve investors supported (20.76%, $p<0.001$). This finding is also confirmed when we regress the percentage of sophisticated investors after Day 1 on the percentage of large investments on Day 1 ($LargePer$) with all the same controls as in equation (2). In Table 11, we obtain a negative and significant coefficient of $LargePer$ in column 1, suggesting that a project attracts fewer sophisticated investors subsequently if it has more large investments on Day 1. In contrast, when we regress the percentage of naïve investors after Day 1 on the percentage of large investments on Day 1 ($LargePer$) with all the same controls as in equation (2), we obtain a positive and significant coefficient of $LargePer$, suggesting that a project is associated with more naïve investors subsequently if it has more large investments on Day 1 (column 2 of Table 11).

One concern is that the regression results may be mechanical due to our constructions of the sophisticated and naïve investor groups. As shown earlier, project fundraising outcomes are better when large Day 1 investments are fewer. When we define sophisticated and naïve investors based on the fundraising outcomes of the projects they support, by construction the projects sophisticated investors support have fewer large Day 1 investments and the projects naïve investors support have more large Day 1 investments. To address the concern, we rank the 12,378 investors based on the fundraising outcomes of the first projects they invest in as an alternative way to define sophisticated and naïve investors. Then we examine the subsequent projects those two groups of investors support. If these two groups of investors do not differ in terms of investing skills, the differences of the fundraising outcomes of the first projects they invest in are purely driven by luck and cannot predict the fundraising outcomes of the subsequent projects they support.

However, our results show the opposite. The subsequent projects that sophisticated investors support have significantly better fundraising outcomes (3.60) than those that naïve investors support (2.08, $p<0.001$) (Table 12). Moreover, the subsequent projects that sophisticated investors support have a significantly smaller percentage of large Day 1 investments (16.84%) than those that naïve investors support (22.66%, $p<0.001$). In addition, we compare the distributions of fundraising outcomes of the subsequent projects that the sophisticated and naïve investors support (Figures 8a and 8b). We find that in both successful and unsuccessful projects, the subsequent projects chosen by sophisticated investors have significantly better fundraising outcomes than those chosen by naïve investors.

Taken together, we find evidence to support the hypothesis that entrepreneurs' strategic financing can only attract naïve investors. On the other hand, sophisticated investors can either discern strategic financing, considering it as an unfavorable signal, and avoid these projects, or they can observe project quality and decline to invest. We also show that these two groups of investors have significantly different investing behavior: while naïve investors herd with the crowd in an uninformed manner, sophisticated investors wait and invest more money at later stages of the campaign.

IV. Conclusion

Our paper studies the information role of financing from friends. Based on social media account login data on a crowdfunding platform, we identify contributions from friends and their contribution dynamic. We show that insider financing is perceived as a signal of manipulation of funding performance, and hence is negatively correlated with quality of projects. Projects that have more contributions from friends are less likely to succeed in fundraising. When projects show moderate early funding performance, entrepreneurs strategically allocate contributions from friends to encourage naïve investors to herd. Entrepreneurs also manipulate contribution when projects are close to reaching AoN targets at the end of a funding campaign. Taking the entrepreneur's strategic moves into account, sophisticated investors view financing from family and friends as a negative signal and are less likely to invest.

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Table A. Variable list

Variable	Meaning
LargePer	The percentage of large investments on day 1
FriendPer	The percentage of friends' investments on day 1
ModerateProjects	A dummy variable that equals 1 if a project's fundraising outcome (measured by "the total amount of money raised divided by the funding goal") is among the second highest of the four-quintiles of all projects; 0 if a project's fundraising outcome is among the highest of the four-quintiles of all projects
Log(FundingGoal)	Log-transformed funding goal of a project
Funding duration	Fundraising duration of a project
Log(FirstAmount)	Log-transformed amount of money raised on day 1
Log(FirstInvestors)	Log-transformed number of investors on day 1
Friendship	A dummy variable that equals 1 if an investor is a friend of a project's entrepreneur and 0 if an investor is not a friend of a project's entrepreneur
Log(CumulativeAmount)	Log-transformed cumulative amount of money raised before an investor's investment day
Log(LastDayAmount)	Log-transformed amount of money raised in the last day before an investor's investment day
NonFriendsInvestments	The number of investments from nonfriends
NonFriendsAmount	The amount of money from nonfriends
Log(NonFriendsInvestments)	Log-transformed number of investments from nonfriends
Log(NonFriendsAmount)	Log-transformed amount of money from nonfriends
FriendLargePer	The percentage of large investments from friends on day 1
AlmostSuccessfulProjects	A dummy variable that equals 1 if, two days before the deadline of the project's fundraising campaign, a project reached more than 50% but less than 100% of its funding goal; 0 if a project reached its funding goal
12 pm. – 14:59 pm.	A dummy variable that equals 1 if it is between 12 pm. and 14:59 pm.; 0 otherwise
15 pm. – 17:59 pm.	A dummy variable that equals 1 if it is between 15 pm. and 17:59 pm.; 0 otherwise
18 pm. – 20:59 pm.	A dummy variable that equals 1 if it is between 18 pm. and 20:59 pm.; 0 otherwise
21 pm. – 23:59 pm.	A dummy variable that equals 1 if it is between 21 pm. and 23:59 pm.; 0 otherwise

Table 1. Descriptive statistics of crowdfunding projects

	Mean	Std.	Min	Max
Funded (1=yes)	0.56	0.50	0	1
Funding goal (RMB)	20,995	91,561.76	200	2,000,000
Total amount raised (RMB)	32,687.27	125,902	20	1,715,688
Total amount raised/Funding goal	4.76	57.92	0.001	1709.44
Duration(days)	42.78	17.58	6	150
No. of investors per project	115.67	340.11	1	5,258
Average investment amount per investor (RMB)	248.45	2369.53	1	500,000

Table 2. Investment amounts from friends vs. external investors

This table reports the results of a linear regression where the dependent variable is the amount of money an investor invests in a project. Friendship is a dummy variable indicating whether an investor is the entrepreneur's friend (1 if yes and 0 otherwise). Table A defines all other variables. Project industry fixed effects and time of a project's launch fixed effects (i.e., which day a project was launched on the crowdfunding platform, from Monday to Sunday) are included in all columns. Standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Variable	(1)
Friendship	233.036***
	(42.859)
Log(FundingGoal)	38.668***
	(6.680)
Funding duration	-1.494***
	(0.383)
Project industry fixed effects	Yes
Time of a project's launch fixed effects	Yes
R^2	0.003
Observations	89538

Table 3. The project launch time (T1) vs. an investor's sign up time (T2)

This table reports the percentage of entrepreneurs'' Weibo friends (vs. non-Weibo friends) whose sign up time is the same as (or within a week of) the entrepreneurs' project launch time.

	T1=T2	0<= T1-T2<=7
Weibo Friends	15.48%	43.11%
Non-Weibo friends	7.74%	25.81%

Table 4. Friendship and large day 1 investments

This table reports the results of a Probit regression. The dependent variable is a dummy variable indicating whether an investor is a friend of the entrepreneur (1 for yes and 0 otherwise). *LargeInvestment* is a dummy variable indicating whether an investment on day 1 is a large amount (1 for yes and 0 otherwise). Table A defines all other variables. Project industry fixed effects and time of a project's launch fixed effects (i.e., which day a project was launched on the crowdfunding platform, from Monday to Sunday) are included in all columns. Standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Variable	(1)
LargeInvestment	0.315***
	(0.068)
Log(FundingGoal)	-0.180***
	(0.027)
Funding duration	0.004***
	(0.001)
Log(FirstAmount)	-0.092**
	(0.042)
Log(FirstInvestors)	-0.200***
	(0.049)
Project industry fixed effects	Yes
Time of a project's launch fixed effects	Yes
R^2	0.247
Observations	2669

Table 5. Day 1 investments and final fundraising outcomes

This table reports the results of two linear regressions. In Model 1, the dependent variable is the log-transformed total amount of money a project raised. In Model 2, the dependent variable is a dummy variable which equals 1 if a project successfully reached its funding goal and 0 if it failed to reach its funding goal. *Log(FirstAmount)* is the log-transformed amount of money raised on Day 1. Table A defines all other variables. Project industry fixed effects and time of a project's launch fixed effects (i.e., which day a project was launched on the crowdfunding platform, from Monday to Sunday) are included in all columns. Standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Variable	(1)	(2)
Log(FirstAmount)	0.615***	0.452***
	(0.042)	(0.064)
Log(FirstInvestors)	0.137**	0.181**
	(0.055)	(0.080)
Log(FundingGoal)	0.152***	-0.533***
	(0.036)	(0.055)
Funding duration	0.009***	0.002
	(0.002)	(0.003)
Project industry fixed effects	Yes	Yes
Time of a project's launch fixed effects	Yes	Yes
R^2	0.692	0.338
Observations	827	827

Table 6. Large day 1 investments and fundraising outcomes

This table reports the results of two linear regressions (models 1 and 2) and one linear probability regression (model 3). In Model 1, the dependent variable is the log-transformed total amount of money a project raised. In Model 2, the dependent variable is the log-transformed total number of investors a project attracted. In Model 3, the dependent variable is a dummy variable that equals 1 if a project successfully reached its funding goal and 0 if it failed to reach its funding goal. *LargePer* is the percentage of large investments on the first day of a project's launch. Table A defines all other variables. Project industry fixed effects and time of a project's launch fixed effects (i.e., which day a project was launched on the crowdfunding platform, from Monday to Sunday) are included in all columns. Standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Variable	(1)	(2)	(3)
LargePer	-1.550***	-0.526***	-1.450***
	(0.108)	(0.088)	(0.187)
Log(FundingGoal)	0.104***	0.004	-0.661***
	(0.033)	(0.026)	(0.062)
Funding duration	0.009***	0.009***	0.003
	(0.002)	(0.002)	(0.003)
Log(FirstAmount)	0.811***	0.086***	0.714***
	(0.040)	(0.033)	(0.078)
Log(FirstInvestors)	-0.161***	0.644***	-0.109
	(0.053)	(0.043)	(0.091)
Project industry fixed effects	Yes	Yes	Yes
Time of a project's launch fixed effects	Yes	Yes	Yes
R^2	0.754	0.680	0.399^
Observations	827	827	827

Table 7. Large day 1 investments and individual investors' investment

This table reports the results of two linear regressions (models 1 and 2). In both models 1 and 2, the dependent variable is the amount of money an investor invested to a project. Table A defines all other variables. Project industry fixed effects, individual investors' fixed effects, time of a project's launch fixed effects (i.e., which day a project was launched on the crowdfunding platform, from Monday to Sunday), and time of an investor's investment fixed effects are included in all columns. Standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Variable	(1)	(2)
LargePer	-0.452***	
	(0.038)	
FriendLargePer		-0.727***
		(0.097)
Log(FundingGoal)	0.073***	0.073***
	(0.008)	(0.008)
Funding duration	0.005***	0.005***
	(0.000)	(0.000)
Log(FirstAmount)	0.405***	0.372***
	(0.013)	(0.013)
Log(FirstInvestors)	-0.574***	-0.546***
	(0.014)	(0.013)
Friendship	0.238***	0.241***
	(0.023)	(0.023)
Log(CumulativeAmount)	0.054***	0.069***
	(0.008)	(0.008)
Log(LastDayAmount)	0.032***	0.035***
	(0.004)	(0.004)
Project industry fixed effects	Yes	Yes
Individual investors' fixed effects	Yes	Yes
Time of a project's launch fixed effects	Yes	Yes
Time of an investor's investment fixed effects	Yes	Yes
R^2	0.704	0.701
Observations	13,338	13,338

Table 8. Large Day 1 investments and funding goal

This table reports the results of a linear regressions (Model 1) where the dependent variable is the funding goal of a project. Table A defines all other variables. Project industry fixed effects and time of a project's launch fixed effects (i.e., which day a project was launched on the crowdfunding platform, from Monday to Sunday) are included. Standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Variable	(1)
LargePer	-0.179
	(0.113)
Funding Duration	0.014***
	(0.002)
Project industry fixed effects	Yes
Time of a project's launch fixed effects	Yes
R^2	0.192
Observations	827

Table 9. Day 1 hourly investments from friends

This table reports the results of two linear regressions. In Model 1, the dependent variable is the percentage of investments that came from friends in three-hour segments of day 1. In Model 2, the dependent variable is the percentage of money that came from friends in three-hour segments of day 1. *ModerateProjects* is a dummy variable that equals 1 if a project's fundraising outcome (measured by "the total amount of money raised divided by the funding goal") is among the second highest of the four-quintile of all projects; 0 if a project's fundraising outcome is among the highest of the four-quintile of all projects. The interaction terms between *ModerateProjects* and time windows (e.g., (12 pm.-14:59 pm.)) show how the effect of *ModerateProjects* changes over time. Table A defines all other variables. Project industry fixed effects, time of a project's launch fixed effects (i.e., which day a project was launched on the crowdfunding platform, from Monday to Sunday), and time of investment fixed effects (i.e., 12pm.-14:59 pm., 15 pm.-17:59 pm., 18 pm.-20:59 pm., and 21 pm.-23:59 pm.) are included in all columns. Standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Variable	(1)	(2)
ModerateProjects	-0.031	-0.052
	(0.043)	(0.045)
ModerateProjects * (12 pm.-14:59 pm.)	0.011	0.027
	(0.049)	(0.052)
ModerateProjects * (15 pm.-17:59 pm.)	0.046	0.072
	(0.049)	(0.052)
ModerateProjects * (18 pm.-20:59 pm.)	0.066	0.095*
	(0.051)	(0.054)
ModerateProjects * (21 pm.-23:59 pm.)	0.091*	0.111**
	(0.049)	(0.052)
Log(FundingGoal)	0.003	0.004
	(0.007)	(0.008)
Funding duration	0.001***	0.001***
	(0.000)	(0.000)
Log(FirstAmount)	-0.003	-0.003
	(0.008)	(0.009)
Log(FirstInvestors)	-0.005	-0.003
	(0.010)	(0.010)
Project industry fixed effects	Yes	Yes
Time of a project's launch fixed effects	Yes	Yes
Time of investment fixed effects	Yes	Yes
R^2	0.175	0.172
Observations	1366	1366

Table 10. Last two days regressions (almost successful projects vs. successful projects)

This table reports the results of four linear regressions. In Model 1, the dependent variable is the log-transformed number of investments made by an entrepreneur's friends. In Model 2, the dependent variable is the log-transformed amount of money made by an entrepreneur's friends. In Model 3, the dependent variable is the number of investments made by an entrepreneur's friends. In Model 4, the dependent variable is the amount of money made by an entrepreneur's friends. *AlmostSuccessfulProjects* is a dummy variable that equals 1 if, two days before the deadline of the project's fundraising campaign, a project reached more than 50% but less than 100% of its funding goal; 0 if a project reached its funding goal. Table A defines all other variables. Project industry fixed effects and time of a project's launch fixed effects (i.e., which day a project was launched on the crowdfunding platform, from Monday to Sunday) are included in all columns. Standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Variable	(1)	(2)	(3)	(4)
AlmostSuccessfulProjects	0.111**	0.312	0.859***	148.924**
	(0.050)	(0.253)	(0.307)	(74.008)
Log(NonFriendsInvestments)	0.026			
	(0.021)			
Log(NonFriendsAmount)		-0.005		
		(0.055)		
NonFriendsInvestments			0.006	
			(0.006)	
NonFriendsAmount				0.001
				(0.003)
Log(FundingGoal)	0.017	0.179*	0.042	44.464*
	(0.018)	(0.095)	(0.106)	(25.321)
Funding duration	-0.002*	-0.012**	-0.003	-2.677*
	(0.001)	(0.005)	(0.007)	(1.576)
Project industry fixed effects	Yes	Yes	Yes	Yes
Time of a project's launch fixed effects	Yes	Yes	Yes	Yes
R^2	0.102	0.121	0.078	0.101
Observations	386	386	386	386

Table 11. Large day 1 investments and sophisticated vs. naive investors

This table reports the results of two linear regressions (models 1 and 2). In Model 1, the dependent variable is the percentage of sophisticated investors a project attracted on each day (excluding day 1). In Model 2, the dependent variable is the percentage of naive investors a project attracted on each day (excluding day 1). *LargePer* is the percentage of large investments on day 1. Table A defines all other variables. Project industry fixed effects and time of a project's launch fixed effects (i.e., which day a project was launched on the crowdfunding platform, from Monday to Sunday) are included in all columns. Standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Variable	(1)	(2)
LargePer	-0.021***	0.046***
	(0.007)	(0.014)
Log(FundingGoal)	-0.007***	0.008*
	(0.002)	(0.004)
Funding duration	0.000*	0.001**
	(0.000)	(0.000)
Log(FirstAmount)	0.005*	-0.042***
	(0.003)	(0.005)
Log(FirstInvestors)	0.004	-0.002
	(0.004)	(0.007)
Project industry fixed effects	Yes	Yes
Time of a project's launch fixed effects	Yes	Yes
R^2	0.321	0.441
Observations	827	827

Table 12. Sophisticated investors vs. naïve investors

This table presents the differences in fundraising outcomes of projects and the percentage of large contributions on day 1 for two types of projects: the projects supported by sophisticated investors and the projects supported by naïve investors. We use the fundraising outcome of an investor's first project to rank investors. The top 20% of investors are grouped as sophisticated investors and the bottom 20% investors are grouped as naïve investors.

	Sophisticated investors			Naïve investors				
	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	P	t
Fundraising outcomes	1670	3.603	2.300	1707	2.084	1.635	0.000	22.073
LargePer	1670	0.168	0.219	1676	0.227	0.234	0.000	-7.435

Figure 1. The distribution of fundraising outcomes

This figure presents the distribution of fundraising outcomes of all projects in our data. The x axis is the fundraising outcomes measured by the total amount of money raised divided by the funding goal of a project. If the fundraising outcome is not less than 1, the project successfully reaches the funding goal; otherwise, it fails to reach the funding goal. The y axis is the number of projects.

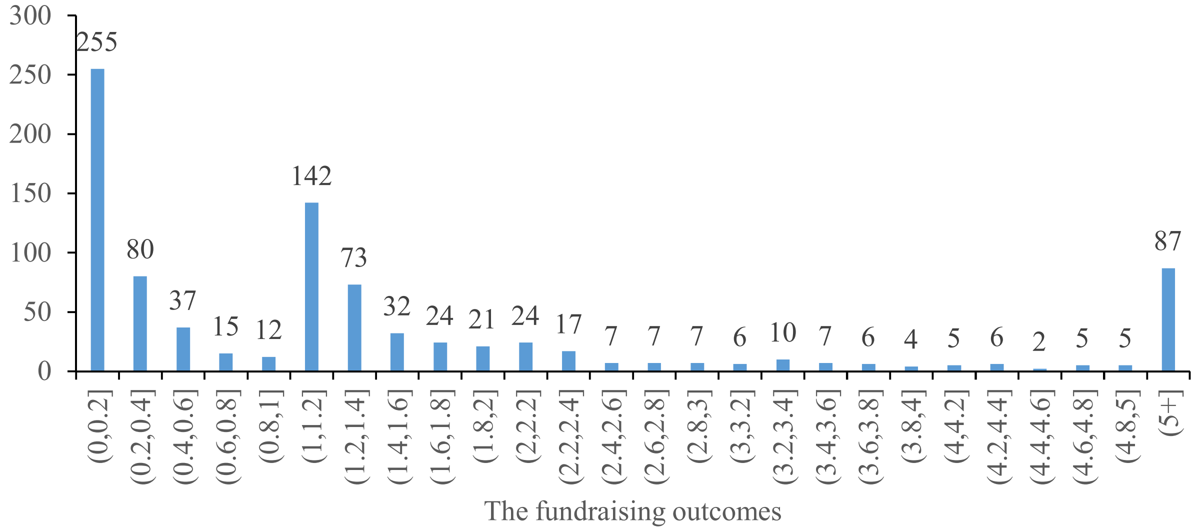


Figure 2a. The percentage of friends' investments on day 1 (de-meaned)

This figure presents the percentage of friends' investments (de-meaned) in every three-hour segment between 9 am. and 23:59 pm. on Day 1 among two groups of projects: good and moderate projects. The x axis is the time on Day 1 and the y axis is the percentage of friends' investments.

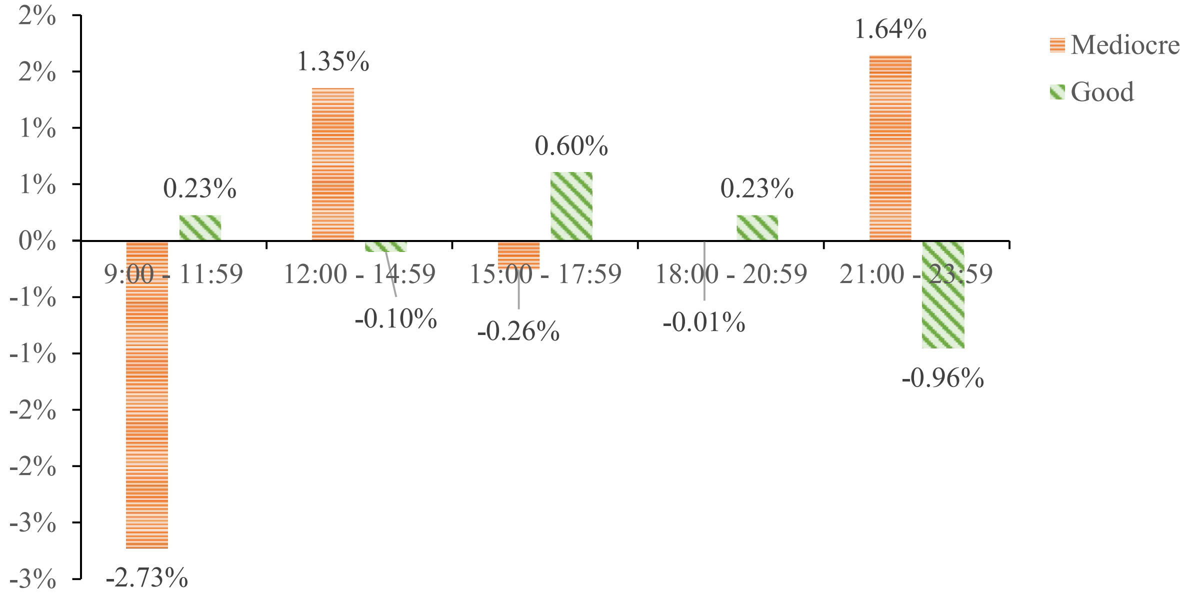


Figure 2b. The percentage of friends' investments on day 1

This figure presents the percentage of friends' investments in every three-hour segment between 9 am. and 23:59 pm. on day 1 among two groups of projects: good and moderate projects. The x axis is the time on day 1 and the y axis is the percentage of friends' investments.

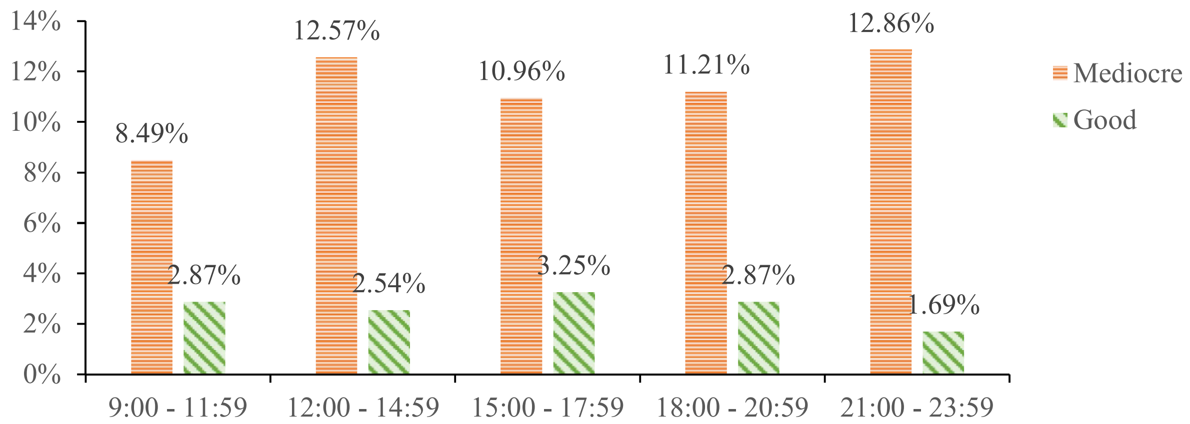


Figure 3a. The percentage of friends' investment amounts on day 1 (de-meaned)

This figure presents the percentage of friends' investment amounts (de-meaned) in every three-hour segment between 9 am. and 23:59 pm. on day 1 among two groups of projects: good and moderate projects. The x axis is the time on day 1 and the y axis is the percentage of friends' investment amounts.

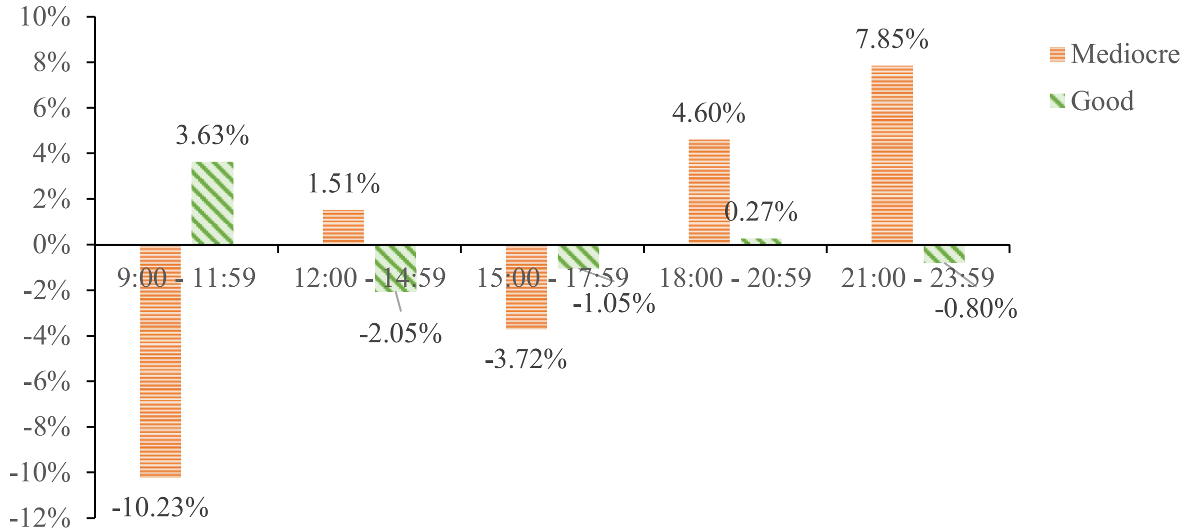


Figure 3b. The percentage of friends' investment amounts on day 1

This figure presents the percentage of friends' investment amounts in every three-hour segment between 9 am. and 23:59 pm. on day 1 among two groups of projects: good and moderte projects. The x axis is the time on day 1 and the y axis is the percentage of friends' investment amounts.

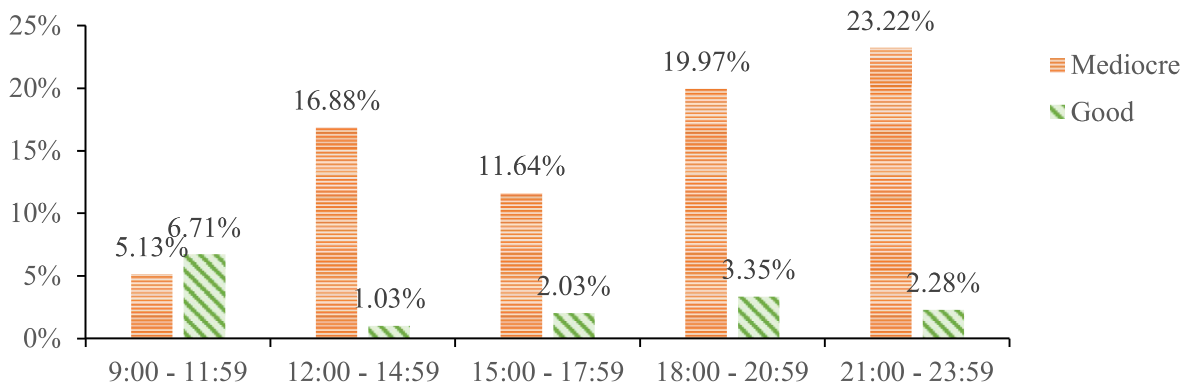


Figure 4a. The percentage of friends' investments on the last two days (de-meaned)

This figure presents the percentage of friends' investments (de-meaned) in half-day segments of the last two days among two groups of projects: successful projects and almost successful projects. The x axis is the time on the last two days and the y axis is the percentage of friends' investments.

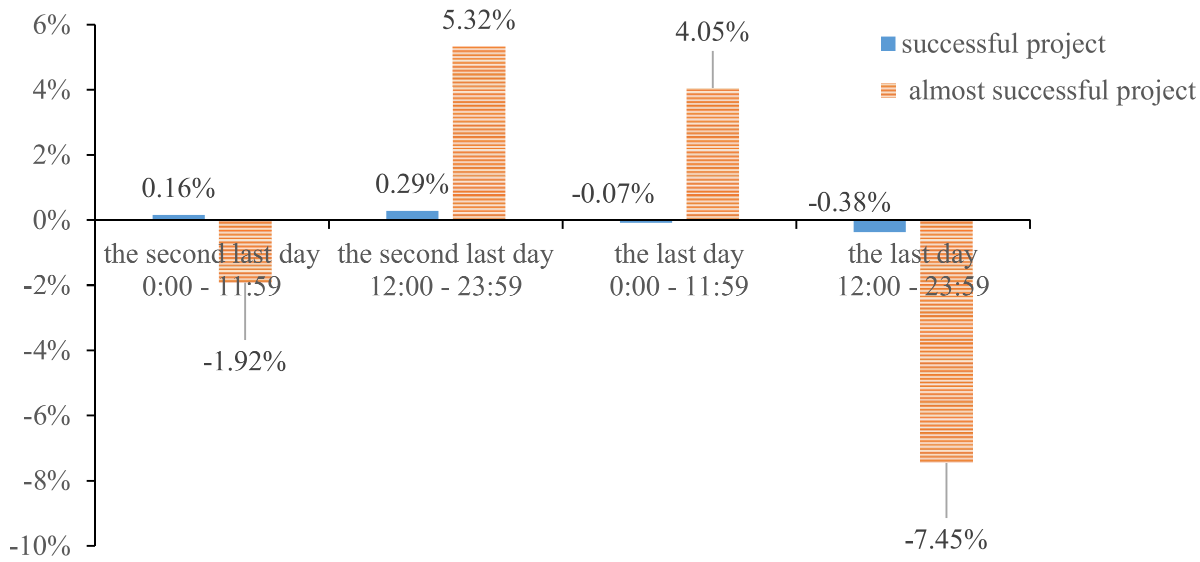


Figure 4b. The percentage of friends' investments on the last two days

This figure presents the percentage of friends' investments in half-day segments of the last two days among two groups of projects: successful projects and almost successful projects. The x axis is the time on the last two days and the y axis is the percentage of friends' investments.

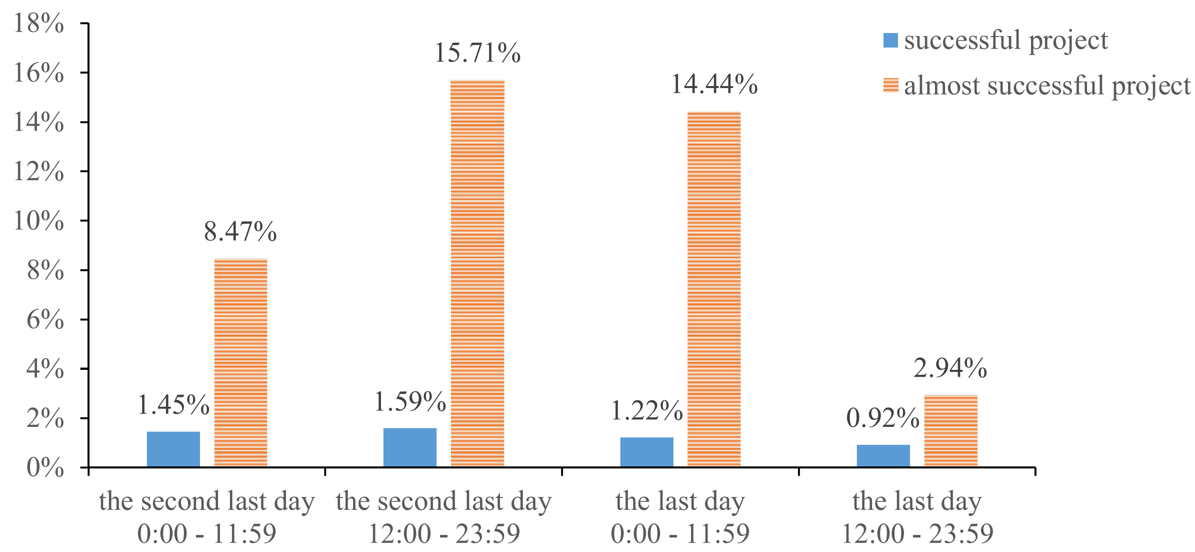


Figure 5a. The percentage of friends' investment amounts on the last two days (de-meaned)

This figure presents the percentage of friends' investment amounts (de-mean) in half-day segments of the last two days among two groups of projects: successful projects and almost successful projects. The x axis is the time on the last two days and the y axis is the percentage of friends' investment amounts.

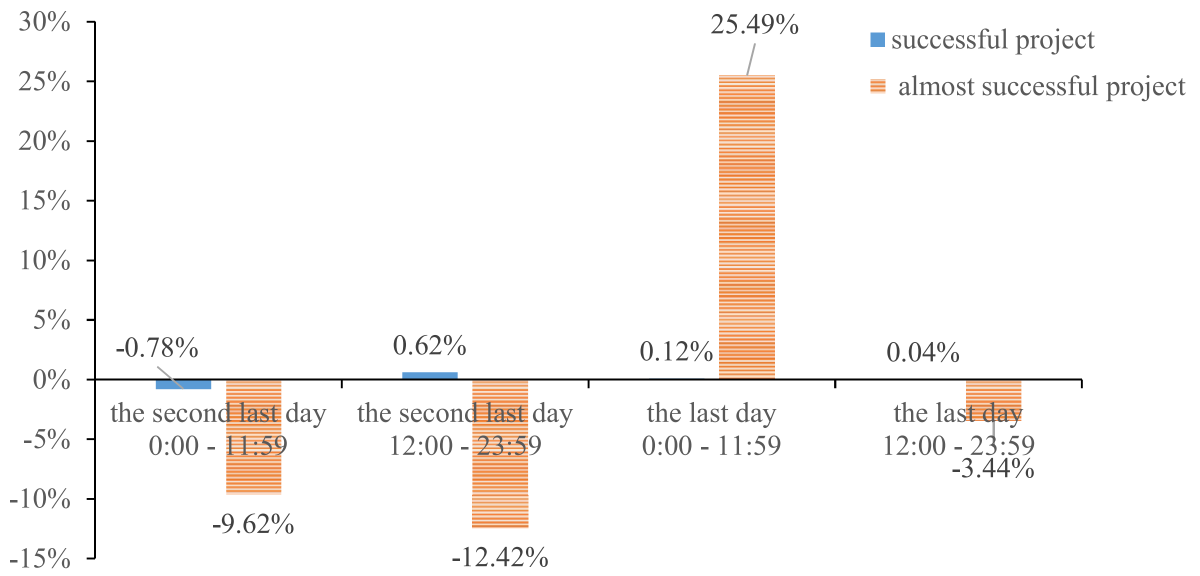


Figure 5b. The percentage of friends' investment amounts on the last two days

This figure presents the percentage of friends' investment amounts in half-day segments of the last two days among two groups of projects: successful projects and almost successful projects. The x axis is the time on the last two days and the y axis is the percentage of friends' investment amounts.

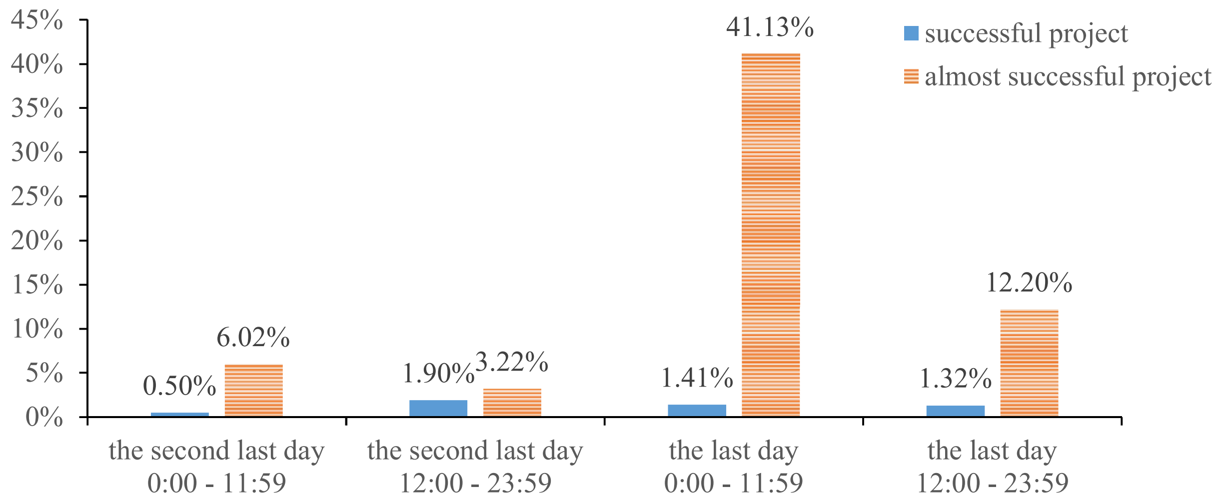


Figure 6. The distribution of investment amounts from sophisticated vs. naive investors

This figure presents the distribution of investment amounts from sophisticated vs. naive investors. The x axis is investment amounts and the y axis is the number of investors.

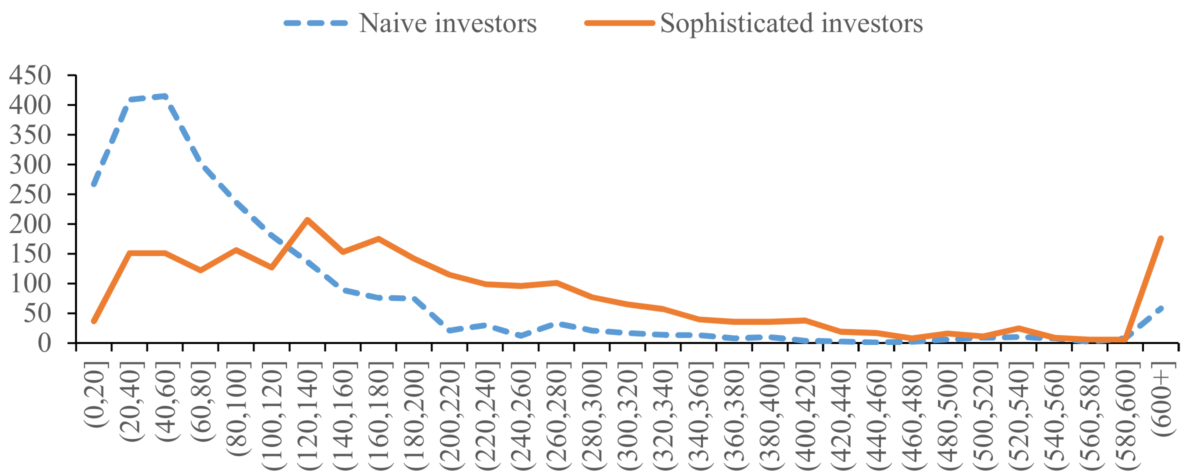


Figure 7. The distribution of investment time of sophisticated vs. naive investors

This figure presents the distribution of investment time of sophisticated vs. naive investors. The x axis is days since the project launch and the y axis is the number of investors.

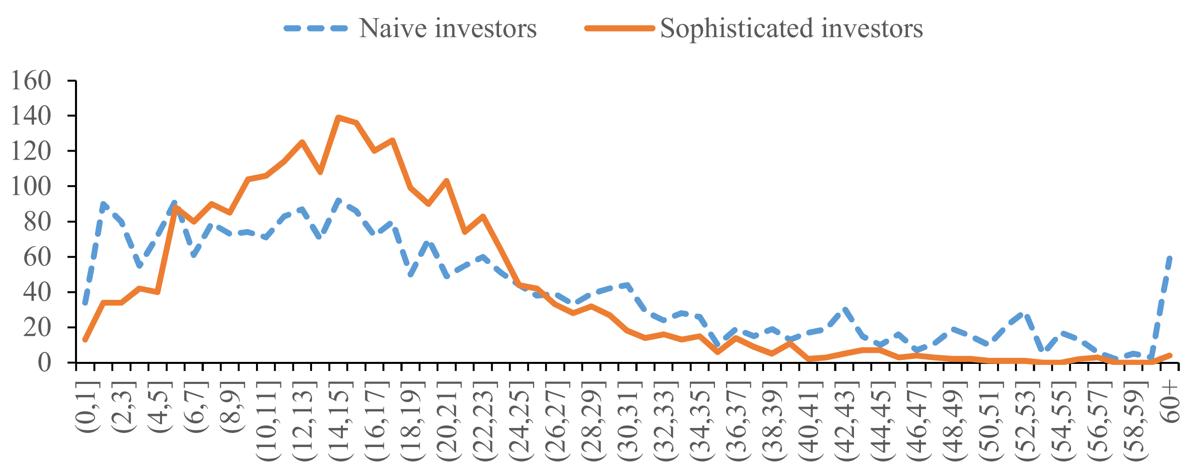


Figure 8a. The distribution of fundraising outcomes of successful projects supported by sophisticated vs. naïve investors

This figure presents the distribution of fundraising outcomes of successful projects supported by sophisticated vs. naïve investors. The x axis is fundraising outcomes (defined as the total amount of money raised divided by the funding goal of a project) of successful projects and the y axis is the number of investors.

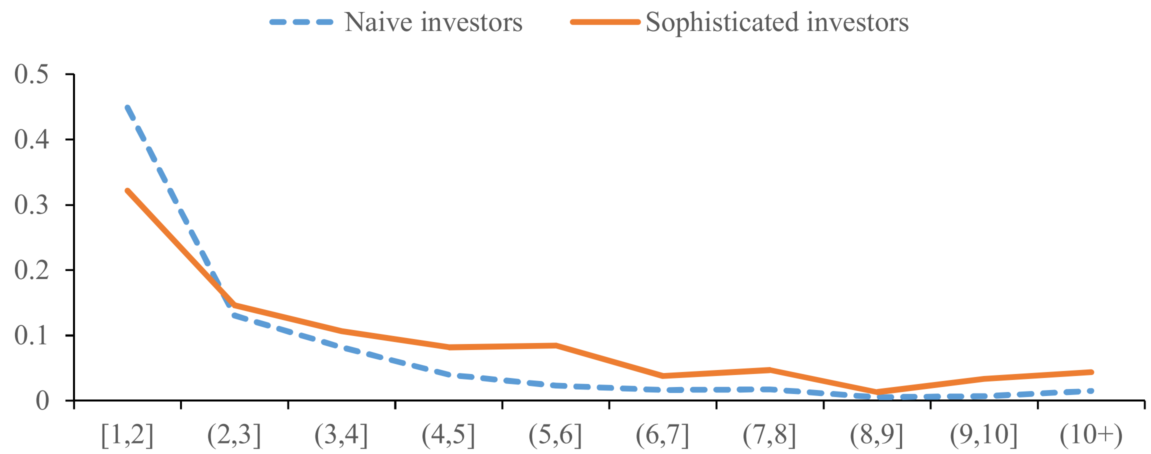
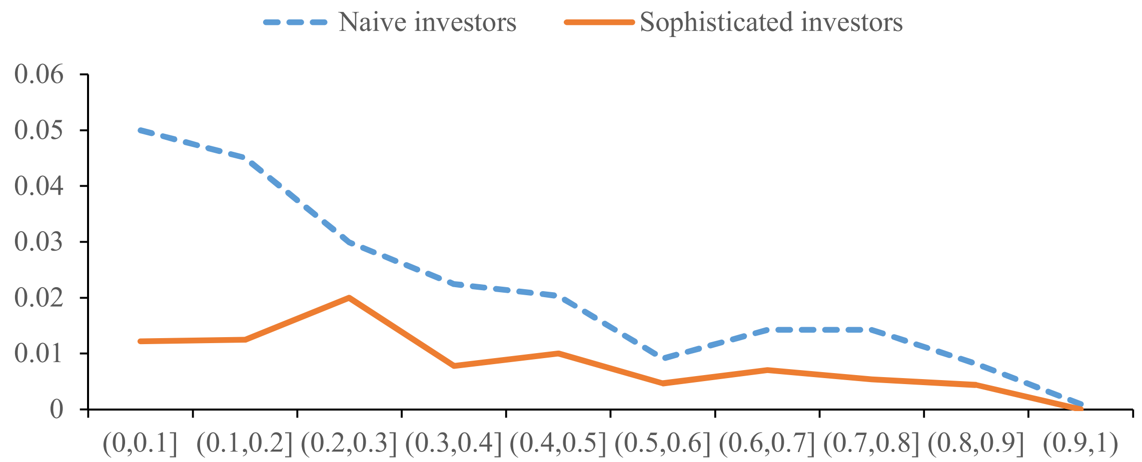


Figure 8b. The distribution of fundraising outcomes of unsuccessful projects supported by sophisticated vs. naïve investors

This figure presents the distribution of fundraising outcomes of unsuccessful projects supported by sophisticated vs. naïve investors. The x axis is fundraising outcomes (defined as the total amount of money raised divided by the funding goal of a project) of unsuccessful projects and the y axis is the number of investors.



Appendix A

Figure 1. A Project on the DemoHour Website

Appendix B

Table 1. Project categories (in RMB)

Project Category	Number of Projects	Mean	Standard Deviation	Median	Min	Max
Art	32	106.67	276.05	28.00	10	6000
Books	61	102.45	152.50	50.00	1	10000
Charity	174	84.10	349.47	40.00	1	33333
Designs	203	52.06	237.13	20.00	1	25000
Music	35	152.34	451.79	50.00	10	10000
Technologies	300	306.05	1236.27	129.00	1	50000
Videos	69	254.94	5906.02	52.00	1	500000
Others	22	41.82	79.34	19.00	10	1459