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The role of expertise in herding behaviors: evidence from a crowdfunding market

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Abstract

The peer economy, such as crowdfunding, democratizes access to tasks available only to professionals. Although the peer economy has gained great popularity in practice, how crowds infer information from their peers, especially from experts, is still under minimal study in academia. Using data from a debt-based crowdfunding platform in China, this study investigates the impact of seasoned predecessors' bids on subsequent investors' decisions and how seasoned and unseasoned investors respond differently to herding signals. We discover that the cumulative lending amount from seasoned predecessors is positively associated with the lending amount of a successor, and such an association is greater if the successor is seasoned. In the repayment process, we find that the lending amount from seasoned investors is positively associated with loan performance, while the lending amount from unseasoned investors is not. Our results contribute to the literature on crowds of wisdom, implying that in a context that requires sophisticated knowledge, extracting hidden talents from experts rather than from crowds is more appropriate.

Keywords Collective intelligence · Debt-based crowdfunding · Herding · Expertise

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1 Introduction

The signature of the "peer economy" is that it democratizes access to service tasks that used to be dominated by professionals, such as house renting (Airbnb), taxi service (Uber and DiDi), crowdfunding (Lending Club), and digital photography (Photostock). This paper focuses on debt-based crowdfunding, where mostly amateur investors collectively lend money to borrowers via an online platform. Debt-based crowdfunding has experienced fast growth worldwide. As of September 30, 2019, LendingClub, the largest debt-based crowdfunding platform in the U.S., originated US$ 40.45 billion in loans. In China, debt-based crowdfunding platforms facilitated more than 8800 billion RMB (US$1250 billion) in loans by the end of October 31, 2019.

The thriving of crowdfunding is premised on "collective intelligence": an army of amateurs, empowered by online platforms, can collectively make good investment decisions [39, 49]. One argument is that there are hidden talents among the amateurs that can make as sound decisions as the professionals but at a fraction of the cost [46], furthermore, even though a single amateur may be inferior to a professional, together they can, however, demonstrate "collective intelligence" that can rival professionals [49].

Collective intelligence is known to work the best when individual participants have local knowledge, and they each make independent judgments [11]. However, almost all real-world crowdfunding platforms violate the condition of independence—an investor in the crowdfunding market does not have to finance the entire amount of a loan request, so they could routinely study decisions made by prior investors and, in many cases, copy such decisions in a phenomenon known as "herding". Research has shown that herding is quite harmful to collective intelligence in that it can magnify the small error made by early decision-makers and cause large uncertainties in market outcomes [39, 49]. When a later decision maker ignores his/her own information and copies prior decisions, the market becomes inefficient in aggregating distributed information and thus greatly undermines collective intelligence [37, 49]. To date, there is little understanding of the degeneration of crowdfunding markets because of observational learning.

Of particular interest is the expertise of investors in the crowdfunding market. ***Expertise,*** a form of “human capital” obtained through professional training or practical experience, reflects an individual’s competence and knowledge in a specific domain [17, 18]. Individuals with high expertise are expected to demonstrate superior performance in a repeatable and reproducible manner [53]. When it comes to the field of the debt-based crowdfunding market, the investor expertise could be reflected by investment *experience* and *performance*. We thereby divide investors into two categories based on their level of expertise: seasoned and unseasoned investors. Investors with rich investment experience and good performance are defined as seasoned investors, while the rest as unseasoned ones [13]. By definition, seasoned investors’ investment decisions are of higher quality than the rest. If participants can somehow identify such seasoned investors in crowds and follow their decisions more than others, the degenerative effect of observational learning can be mitigated. Moreover, if seasoned investors act more independently than others, then the informational efficiency of crowdfunding markets will be higher. Therefore, how seasoned investors are leveraged and act in crowdfunding markets holds important implications. These issues are the focus of this paper.

There are several reasons to argue that seasoned investors may not act or be viewed differently in debt-based crowdfunding markets. First, it may be difficult to tell the hidden talents in the crowds. After all, investment outcomes are highly uncertain and, in many cases, delayed, and it may not be clear which investor has higher expertise. Second, amateur investors may lack the sophistication or attention bandwidth to research the profiles of many investors before them (i.e., predecessors). As a result, they may opt for other more accessible cues to aid their decisions. Third, seasoned investors may not have incentives to let others free ride and thus may disguise their expertise from others for strategic gains.

Given the gap in the understanding of experts' role in the debt-based crowdfunding market, we ask the following two questions: (1) Do seasoned and unseasoned predecessors have different influential power? (2) Do seasoned and unseasoned investors differ in interpreting the same market signal?

Drawing on signaling theory [1] and heuristic–systematic information processing theory [5], we hypothesize that investors with greater expertise will be more influential than other investors and are more likely to make independent investment decisions. We then test these hypotheses using a dataset from a leading debt-based crowdfunding lending platform in China.

2 Literature review

2.1 The role of expertise in the market

Our study draws upon research relating to the role of expertise in the market. Current studies have shown that expertise can be reflected in a variety of facets, such as opinion leaders, word-of-mouth, and tagged experts [29, 34]. For instance, people make decisions in e-commerce utilizing diverse information, among which consumers' comments and recommendations, especially opinion leaders, are typical (e.g., [12, 19]). Online information (e.g., recommendations) from different sources may influence consumer choices in different ways because consumers may consider that their credibility varies [24]. Information from high-credibility referents will be more influential and will be more likely to be accepted. Expertise and trustworthiness are the major sources of information credibility [27, 35], so reviewers' expertise and trustworthiness positively affect consumers' behaviors, such as their attitudes toward a brand, purchase intention, and actual purchases (e.g., [41, 51]).

Although experts were found to have important persuasion power, making choices completely following experts may have two limitations. First, it is difficult for consumers to identify who are real experts. Second, experts sometimes only have very limited information or expertise on specific topics. Compared to what has been found in the marketing field, there is very limited research on the value of individual experts in the crowdfunding market. After examining industry practices of crowd designs across countries and reviewing relevant literature on this topic, Chen et al. [10] identified several inefficiencies of pure crowds in crowdfunding platforms and proposed that these shortcomings could be mitigated by a hybrid crowd design. Keongtae and Viswanathan [29] pointed out that special attention should be given to influential entities such as investment banks, experienced venture capitals, and top-ranked mutual funds. Drawing on the dataset of individual investments in a mobile application (app) crowdfunding market, they investigated whether early investments work as signals of quality for later investors and whether the value of these signals differs depending on the identity of early investors. They found that two categories of experts, app development investors and experienced investors, have significant influences on subsequent investors. Furthermore, experts' investment choices are indeed credible to predict apps ex-post performance, sales, and consumer ratings [29]. However, they do not differentiate the response behaviors of signal receivers.

The collective intelligence of crowds, especially end-users, also gains attention. Findings based on the reward-based crowdfunding platform Kickstarter indicate a significant agreement between the investment decisions of nonexperts (investors in Kickstarter) and experts (industrial professionals). There are no quantitative or qualitative differences in the long-term outcomes (e.g., ticket sales and critical reviews in press) between projects funded by both nonexperts and experts and those funded only by nonexperts [38]. These results suggest that nonexperts also play an important role in project evaluation and that their decisions could complement expert decisions.

2.2 Herding behaviors

Our study also draws upon work on herding behavior in the market. In a typical debt-based crowdfunding market, any verified user is eligible to register on the platform as a borrower or an investor [9]. A borrower could post a loan request, called a listing, on the crowdfunding platform, specifying listing terms such as the amount requested, the interest rate offered, loan purpose, loan duration, and information about its borrower. Potential investors could bid when it is open for auction. An investor does not have to finance the entire amount of a loan request,instead, they can bid at a minimum amount specified by the platform [36]. Investors make their investment decision based on their evaluation of the information shown on the platform, including the lending amount from peer predecessors, which makes herding behavior among investors possible (e.g., [4, 28, 56]).

A stream of research focuses on the existence of herding behavior in the market and its rationality. Herding behavior among investors is a ubiquitous phenomenon [21, 44]. Herzenstein et al. [23] discovered the existence of strategic herding behavior among investors, arguing that they have a greater tendency to bid on an auction with more bids, but only to the point at which it has received full funding. They also discovered a positive association between the herding level in the auction period and the subsequent loan performance. Zhang and Liu [56] also discovered evidence of herding among lenders. That is, well-funded borrower listings tend to attract more funding. Their study confirms that lenders engage in active observational learning rather than passively mimicking their peers. Herding behaviors among lenders in the crowdfunding market are observed in other places, such as South Korea and China (e.g., [32, 36, 54, 57]). Studies have shown that herding among lenders is irrational in China, as it is negatively associated with loan performance (Chen and Lin [8]).

Another stream of research focuses on how investors follow the herd. When information on borrower creditworthiness is limited, investors tend to seek information from peer predecessors, and they switch to their own judgment when more signals are transmitted through the market [54]. Liu et al. [36] revealed that when offline friends of a potential lender place a bid, a relational herding effect occurs, as potential lenders are likely to follow their offline friends with a bid. Similarly, in the field of online reviews, community herding also occurs on high ratings, inducing subsequent users to provide high ratings, and such herding behavior will be reduced by the number of friends who have rated the same product [33].

The above studies imply that herding behavior serves as a signal of borrower creditworthiness for potential investors in the crowdfunding market, and it has a significant impact on a successor's decisions. However, prior studies generally assume that herding signals are produced by homogeneous investors, and their influences on successors are also homogeneous. Whether the lending amount from different peer predecessors would have different impacts on successors and whether different investors respond differently to the same herding signals are still under limited study.

3 Theoretical framework and hypothesis development

3.1 Theoretical framework

The usefulness of a market signal depends on two factors: (1) the quality of the signal (i.e., how a market signal is produced) and (2) the processing procedure of the signal (i.e., how the market signal is interpreted by receivers). This study is thus based on two well-established theories: signaling theory [1] and heuristic–systematic information processing theory [5]. Signaling theory is developed based on the seminal work of Akerlof [1] on the used car market, which studied the role of information asymmetry between sellers and buyers and how such information asymmetry between these two parts can lead to adverse selection problems. Such an adverse selection problem can be mitigated if high-quality sellers can produce signals to communicate their superior quality [47]. Credible signals can be observed and can help buyers separate high-quality sellers from low-quality sellers, and ex-post, such signals can be validated to be useful. As crowdfunding is a special type of peer economy, most of the investors in this market are, unlike professional investors in the traditional financial market, less sophisticated [29]. Thus, investors may proactively search and utilize market signals, such as bids from prior investors, to improve decision making. As bids may be from predecessors of different expertise, successors may distinguish the investment amount between from seasoned and from unseasoned investors.

In addition to signaling theory, heuristic–systematic information processing theory is also considered in our research to explain how investors interpret the market signal of prior bids. According to heuristic–systematic information processing theory, information processing is a dual process. There are two different cognition patterns for information processing that require different degrees of cognitive effort: systematic processing and heuristic learning or intuition [14]. Systematic processing is information-intensive and analytically oriented, while heuristic processing is based on simple decision rules with a focus on easily acquired and processed information. Investors may choose between these two cognition patterns according to their knowledge base and their levels of involvement [26, 40]. A heuristic strategy has the economic advantage of requiring a minimum of cognitive effort, while its disadvantage is that it may be less reliable. As systematic processing is difficult and requires effort, unseasoned investors tend to have greater inclinations to adopt a heuristic approach, such as following peers' investment decisions, especially when their issue involvement is low.

Based on the above analysis, the conceptual model is developed as follows (Fig. 1).

3.2 Hypothesis development

Expertise is a form of "human capital" accumulated through professional training and practical experience and indicated by the achievement of superior performance [10]. In the context of debt-based crowdfunding, an investor's expertise grows as the individual's experience of investment activities increases, and investors with different levels of expertise have different capabilities and strategies to process information, which leads to different decision qualities [38]. Compared with unseasoned investors, seasoned investors are more likely to systematically collect relevant information, analyze the true merits of the loan request, and make rational decisions [42]. Thus, seasoned investors might have a better judgment of the information related to a listing. The signal produced by seasoned predecessors would be regarded as more credible than unseasoned signals [52]. In the equity-based crowdfunding platforms, studies have shown that the proportion of funding invested by lead investors in the funding target and their investment experience are positively related to fundraising performance [45]. Thus, in the debt-based crowdfunding platforms, investments from seasoned investors, working as an important market signal, may also

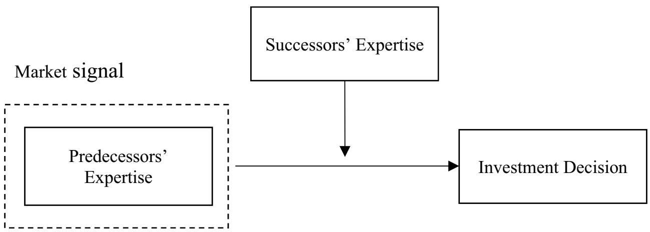


Fig. 1 Conceptual model

exert a much stronger influence on potential investors than unseasoned investors. The investment history and performance of an investor are publicly available on most lending platforms,therefore, seasoned investors, although not explicitly tagged, could be distinguished from unseasoned investors, and the herding signals they produce will be given more weight by potential investors. Thus, we propose the following hypothesis.

Hypothesis 1 The cumulative lending amount made by seasoned predecessors will attract more lending amount from a successor toward a listing than the cumulative lending amount made by unseasoned predecessors.

The effectiveness of a market signal relates not only to its informativeness but also to the information extraction capabilities of its receivers. According to heuristic–systematic information process theory, individuals who are experienced and knowledgeable tend to adopt a systematic way to process all the available information before making decisions, while those who are less experienced tend to place more weight on noncontent cues [42]. Therefore, unseasoned investors have greater inclinations to follow peer investors. Studies in the context of online purchases have confirmed that opinion seekers' expertise level does affect their decisions. For instance, product experts feel that they are more confident in their ability to make a wise choice, and they conduct little external consultation. In contrast, inexperienced consumers are more likely to doubt their ability to make a good purchasing decision, so they tend to learn from others' advice [50]. Thus, we further argue that unseasoned investors are more likely to rely on predecessors' decisions than seasoned investors. This is because unseasoned investors in debt-based crowdfunding are less capable of processing and interpreting diverse information about a loan or a borrower in a systematic way. As a result, they are more reliant on inferring prior experts' decisions. Using data from a project crowdfunding platform, Keongtae and Viswanathan [29] have shown that the crowd investors, although inexperienced, are rather sophisticated in their ability to identify nuanced differences in the underlying expertise of the early investors. Thus, unseasoned investors might be more sensitive than seasoned investors to the herding signal and would give more weight to the lending amount from seasoned predecessors. Thus, we propose that,

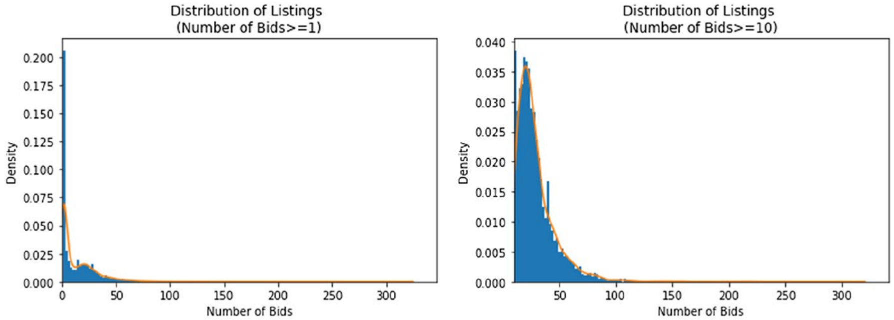
Hypothesis 2 The positive effect of seasoned predecessors on herding is stronger among successors of unseasoned investors than among successors of seasoned investors.

4 Data and methodology

4.1 Research context and data

The research context is one of the leading debt-based crowdfunding platforms in China. This platform started operations in 2007 and now has more than 500,000 registered members. A user could register and create their loan request, called a listing. They need to specify the amount they seek, the interest rate they can offer, and other optional information, such as loan descriptions. Borrowers can choose the auction format of their listings as either open or closed. In the closed-auction format, the auction closes as soon as the total amount raised exceeds the requested amount, while in the open-auction format, investors could continue to bid down the interest rate even if the listing is fully funded. Lenders, known as investors, make lending decisions based on the information displayed on the lending platform. They can choose to bid on any listings that are open for auction. Each bid on a listing is called a transaction. They can finance only a small portion of a listing, so a potential investor could observe prior investors' decisions and their profiles just by clicking some hyperlinks.

The data were collected from the crowdfunding platform in 2017. We obtained 13,911 listings, among which 10,189 were active listings that received at least one bid. The distribution of the number of bids of these listings is shown in Fig. 2a. A large proportion of listings received only a few bids; therefore, we restrict our sample to listings that received at least ten bids to ensure the possibility of herding behaviors. The resulting dataset of our main analysis contains 4372 listings, which attracted a total of 311,163 bids from 3205 distinct investors. The distribution of the number of bids of the sample is shown in Fig. 2b. The panel data are constructed at the transaction (i.e., bid) level by following Jiang et al. [28]'s procedure. For each bid, we collect characteristics at the listing, borrower, and transaction levels. Listing characteristics include the amount requested, the interest rate, the loan duration, the credit grade, the loan title, and the loan purpose. Borrower characteristics include each borrower's age, education level, marriage status, gender, and the number of children. Characteristics of a bid include the investor's lender score, the lending amount, the sequential index of the transaction associated with a given loan, and whether the transaction is conducted by a human being or by the algorithm set by an investor (i.e., autobid). Among the 4372 listings, 1762 are fully funded and turn into loans.



(a) (b)

Fig. 2 The distribution of listings

Next, we describe how “seasoned” and “unseasoned” investors are operationalized. We use the indicator ***lender score*** as a proxy of investor expertise. This score is calculated by the platform according to the following algorithm: (1) each valid bid made on a listing would bring the investor 2 points, (2) if the listing could be fully funded and turn into a loan, then each full monthly repayment of that loan would bring another 2 points, and (3) each repayment overdue of the loan, however, would deduct 10 points. The lender score is thus an appropriate indicator of investment expertise. Investors whose scores are among the top 10% are regarded as “seasoned” investors, while the rest are regarded as “unseasoned” investors.

We report the definition and summary statistics of our main variables in Table 1. An average listing request is RMB 5960 with an interest rate of 17.38% and receives an amount of RMB 229 per transaction. Each borrower will be assigned a credit score derived by the platform based on borrower demographics, verification documents, and repayment records. The dummy variable of credit risk takes a value of 1 if a listing is assigned a low credit rating by the platform (i.e., E or HR) and 0 otherwise (i.e., A, B, C, or D). Approximately 31.5% of the listings were in the category of “risky”. Regarding loan purposes, approximately 42.0% are for “short-term turnover debt”, 31.6% are for “goods consumption”, 10.5% are for “enterprise startup”, 13.1% are for “other purposes”, and the remaining 2.9% do not report loan purpose. The age of borrowers ranges from 19 to 60, with an average value of 29.6. The number of children of borrowers ranges from 1 to 5, with an average value of 1.42. Approximately 38.3% of the borrowers had attended colleges, 46.2% did not report educational levels, 16% were female, and 49.4% were married.

4.2 Research design

A test of herding is to look for the sequential correlation in the herding amount [28, 56]. If herding exists, a positive correlation is expected to be seen between (1) the lending amount of a given bid and (2) the cumulative lending amount the listing has received prior to this bid [28, 55, 56]. Using the transaction-level dataset, we can observe the sequential order of all bids of a listing and construct the herding measure, the cumulative lending amount made to a listing up to any given point of time.

We denote i the investor and j the listing. The logarithm of the lending amount of the tth bid made to listing j by investor i is y_{ijt}, which is modeled as:

$$y_{ijt} = \alpha + \beta Y_{j,t-1} + X_{jt}\gamma_1 + Z_j\gamma_2 + W_i\gamma_3 + \epsilon_{ijt} \quad (1)$$

where t=2, …, T and T is the total number of bids for listing j, and $Y_{j,t-1}$ denotes the logarithm of the cumulative lending amount that listing j has received prior to the tth bid. The parameter β is the magnitude of herding. A positive and significant estimate of β indicates the existence of herding, as it means that subsequent investors’ lending amount is increasing with the cumulative lending amount made to the same listing.

The time-variant listing characteristics $X_{j,t}$ include the percentage of the unfunded amount prior to the tth bid (*Lag Percent Needed*), the time gap between two consecutive transactions (*Time Interval*), the dummy variable indicating a

Table 1 Variable description and summary

Variable	Description	Mean	SD	Min	Max
Listing-level characteristics					
Amount requested	Request amount of a loan (RMB)	5960.014	5677.953	3000.000	100,000
Interest rate	Interest rate provided by a borrower (%)	17.38	3.865	5.000	22
Loan duration	The number of months for repayments	5.215	3.468	1.000	18
Title length	The number of characteristics in the listing title	18.843	5.914	10.000	30
Credit risky	1 if a listing's credit rating is E or HR, 0 otherwise	0.315	0.465	0.000	1
Num of bids	Total number of bids a listing receives	29.108	17.191	10.000	217
Purpose (base)	The purpose of a loan is for goods consumption	0.316	0.465	0.000	1
Purpose (enterprise startup)	The purpose of a loan is for enterprise startup	0.105	0.306	0.000	1
Purpose (other purpose)	The purpose of a loan is for other purpose	0.131	0.337	0.000	1
Purpose (short-term turnover debt)	The purpose of a loan is for short-term turnover debt	0.420	0.494	0.000	1
Purpose (not reported)	The purpose of a loan is not reported	0.029	0.167	0.000	1
Borrower-level characteristics					
Age	The age of the borrower	29.567	6.072	19.000	60
Num of children	The number of children the borrower has	1.429	0.59	1.000	5
Education (base)	The borrower has a college diploma or higher	0.383	0.486	0.000	1
Education (low)	The borrower has a high school diploma or lower	0.154	0.362	0.000	1
Education (not reported)	The borrower education level is not reported	0.462	0.499	0.000	1
Gender (base)	The borrower is a female	0.16	0.367	0.000	1
Gender (male)	The borrower is a male	0.84	0.367	0.000	1
Marriage (base)	The borrower has married	0.496	0.5	0.000	1
Marriage (single)	The borrower has not married	0.484	0.5	0.000	1
Marriage (not reported)	The borrower's marriage status is not reported	0.02	0.138	0.000	1
Bid-level characteristics					
Bid amount	The investment amount of a bid	228.969	547.495	50.000	80,000
Percent needed	The percentage of unfunded amount (%)	0.488	0.312	0.000	1

Table 1 (continued)

Variable	Description	Mean	SD	Min	Max
Time interval	The time gap between two consecutive bids (seconds)	116.368	350.285	0	23,220.54
Late fundraising stage	1 if percentage of unfunded amount is less than 50%, 0 otherwise	0.515	0.5	0.000	1
Auto bid	1 if a bid is made by an algorithm predefined by an investor, 0 otherwise	0.069	0.254	0.000	1
Seasoned	1 if the investor is seasoned, 0 otherwise	0.673	0.469	0.000	1

listing is situated in its late fundraising stage if the percentage of the unfunded amount is less than 50% (*Late Fundraising Stage*), and whether a bid is made by an algorithm (*Auto Bid*). To capture the possibility that lending concentrates on certain days of a week, we further include *Day of Week* fixed effects. Time-invariant listing and borrower characteristics Z_j include *Amount Requested*, *Interest Rate*, *Loan Duration*, *Title Length*, *Credit Risky*, *Purpose*, *Age*, *Num of Children*, *Education*, *Gender*, and *Marriage*. We include in W_i a dummy variable that indicates whether a bid is made by a seasoned investor (*Seasoned*). The error term is ϵ_{ijt}.

We decompose $Y_{j,t-1}$ into $Y^s_{j,t-1}$ and $Y^u_{j,t-1}$ to further differentiate the heterogeneous herding effects induced by seasoned and unseasoned predecessors. $Y^s_{j,t-1}$ and $Y^u_{j,t-1}$ denote the logarithm of the cumulative lending amount made by "seasoned" predecessors and "unseasoned" predecessors, respectively. Accordingly, we enhance Model (1) as follows:

$$y_{ijt} = \alpha + \beta_s Y^s_{j,t-1} + \beta_u Y^u_{j,t-1} + X_{jt}\gamma_1 + Z_j\gamma_2 + W_i\gamma_3 + \epsilon_{ijt} \tag{2}$$

where β_s and β_u measure the subsequent investor's herding momentum toward predecessors who are seasoned and unseasoned, respectively. The relative magnitude of these two coefficients will inform us of the role of investor expertise in investors' observational learning process [28].

The variation in lending amounts could be attributed to some higher-level sources of variation where each bid resides. There could be unobserved heterogeneity beyond the observable listing characteristics that we have controlled for, and investors with different characteristics may also have different investment behaviors. Ignoring these unobserved heterogeneities could produce an inconsistent estimation [28]. We, therefore, use a cross-classified multilevel modeling approach to address this concern, as suggested by Jiang et al. [28]. As we can observe the bids made to different listings from distinct investors, the bids can be viewed as lowest-level units nested within higher levels: listings and investors, but listings and investors are not nested within each other. Accordingly, we enhance Models (1) and (2) by inserting investor-specific intercepts (η_{i}) and listing-specific intercepts (η_j) to better controls for unobserved heterogeneity at the investor and listing levels, respectively. Thus, we rewrite the model for herding analysis as:

$$y_{ijt} = \alpha + \beta Y_{j,t-1} + X_{jt}\gamma_1 + Z_j\gamma_2 + W_i\gamma_3 + \eta_i + \eta_j + \epsilon_{ijt} \tag{3}$$

where $\eta_j \sim N\left(0, \sigma^2_{\eta_i}\right)$ and $\eta_j \sim N\left(0, \sigma^2_{\eta_j}\right)$. $\sigma^2_{\eta_i}$ and $\sigma^2_{\eta_j}$ are the variance of parameters that represent the degree of heterogeneity at the investor and listing level, respectively. The model testing the role of investor expertise in herding is finally expressed as:

$$y_{ijt} = \alpha + \beta_s Y^s_{j,t-1} + \beta_u Y^u_{j,t-1} + X_{jt}\gamma_1 + Z_j\gamma_2 + W_i\gamma_3 + \eta_i + \eta_j + \epsilon_{ijt} \tag{4}$$

To test Hypothesis 2, we enhance Model (3) and Model (4) by allowing herding measures to interact with the variable *Seasoned*.

5 Results

5.1 Estimation results

Table 2 presents the estimation results. We first examine whether herding behavior exists in our research context. Column (1) of Table 2 reports the parameter estimates specified in Model (3). The estimated coefficient of Y is positive and significant, confirming the existence of herding among investors. Such results are consistent with prior studies ([28, 2374, 56]).

We next test our hypothesis about the role of investor expertise in herding (Hypothesis 1). Column (2) of Table 2 reports parameter estimates from Model (4). The estimated coefficient of Y^s is positive and statistically significant, while the estimated coefficient of Y^u is negative and statistically significant. Such findings imply that investors herd only to seasoned predecessors, while unseasoned predecessors' lending amount is regarded as a negative signal. To verify whether the two estimates are significantly different from each other, we test a null hypothesis: $\beta_s - \beta_u = 0$. The result rejects the null hypothesis ($p < 0.001$). The above findings show that Hypothesis 1 is supported.

The results for testing Hypothesis 2 are presented in Columns (3)–(5) of Table 2. In Column (3), we find that the estimated coefficient of the interaction term Y × Seasoned is positive and statistically significant, and the coefficient of Y becomes very weak. Such results imply that, compared to unseasoned investors, seasoned investors are more likely to herd to peer predecessors. We then proceed to examine the heterogeneous impact of seasoned predecessors on seasoned and unseasoned investors. In Column (4) in Table 2, the estimated coefficient of the interaction term $Y^s \times Seasoned$ is positive and statistically significant, and in Column (5) in Table 2, the estimated coefficient of the interaction term $Y^u \times Seasoned$ is negative and statistically insignificant. Such findings show that compared to unseasoned investors, seasoned investors are more likely to herd to seasoned predecessors, and they are more likely to take the cumulative lending amount from unseasoned predecessors as a negative signal. Such findings indicate that Hypothesis 2 is not supported.

Our findings extend the conventional view of the wisdom of the crowd. Prior studies have shown that individual participants have local knowledge and that collective intelligence can be extracted by observational learning [11, 38, 56]. In contrast to this point of view, our results show that observational learning takes place only among seasoned investors in our research context. Unseasoned investors, on the contrary, can hardly notice the value of such market signals. They make decisions based on their own independent judgments. Moreover, our findings show that the market influences of peer predecessors are heterogeneous. Herding effects are mainly induced by seasoned predecessors, and unseasoned predecessors' decisions, on the contrary, are recognized as negative market signals.

Table 2 Main analysis

	(1) Herding	(2) Decomposition	(3) Interaction I	(4) Interaction II	(5) Interaction III
Y: All predecessors	0.0463*** (0.0044)		0.0099* (0.0057)		
Y^s: Seasoned predecessors		0.0197*** (0.0029)		−0.0128*** (0.0040)	0.0203*** (0.0029)
Y^u: Unseasoned predecessors		−0.0166*** (0.0009)		−0.0170*** (0.0009)	−0.0115*** (0.0017)
Lag percent needed	0.1158*** (0.0206)	−0.0833*** (0.0180)	0.1007*** (0.0207)	−0.0850*** (0.0180)	−0.0804*** (0.0181)
Late fundraising stage	0.0214*** (0.0077)	0.0015 (0.0076)	0.0214*** (0.0077)	0.0032 (0.0076)	0.0015 (0.0076)
Auto bid	0.3212*** (0.0090)	0.3014*** (0.0091)	0.3217*** (0.0090)	0.3007*** (0.0091)	0.3003*** (0.0091)
Time interval	−0.0098*** (0.0021)	−0.0100*** (0.0021)	−0.0107*** (0.0021)	−0.0107*** (0.0021)	−0.0097*** (0.0021)
Seasoned (1 = yes)	0.1164*** (0.0262)	0.1055*** (0.0263)	−0.2045*** (0.0419)	−0.2061*** (0.0376)	0.1422*** (0.0282)
Amount requested	0.1103*** (0.0057)	0.1540*** (0.0049)	0.1157*** (0.0057)	0.1556*** (0.0049)	0.1529*** (0.0049)
Interest rate	−0.0029*** (0.0006)	−0.0029*** (0.0006)	−0.0028*** (0.0006)	−0.0029*** (0.0006)	−0.0030*** (0.0006)
Loan duration	−0.0014** (0.0007)	−0.0037*** (0.0007)	−0.0013* (0.0007)	−0.0036*** (0.0007)	−0.0037*** (0.0007)
Credit risky	−0.0154*** (0.0051)	−0.0124** (0.0051)	−0.0165*** (0.0051)	−0.0135*** (0.0051)	−0.0122** (0.0051)
Title length	−0.0023*** (0.0003)	−0.0020*** (0.0003)	−0.0023*** (0.0003)	−0.0020*** (0.0003)	−0.0020*** (0.0003)
Purpose (enterprise startup)	0.0093 (0.0067)	0.0124* (0.0067)	0.0092 (0.0067)	0.0122* (0.0067)	0.0124* (0.0067)

Table 2 (continued)

	(1) Herding	(2) Decomposition	(3) Interaction I	(4) Interaction II	(5) Interaction III
Purpose (other purpose)	0.0259*** (0.0064)	0.0263*** (0.0064)	0.0260*** (0.0064)	0.0268*** (0.0064)	0.0264*** (0.0064)
Purpose (short-term turnover debt)	0.0030 (0.0046)	0.0031 (0.0046)	0.0029 (0.0046)	0.0032 (0.0046)	0.0032 (0.0046)
Purpose (not reported)	0.2689*** (0.0120)	0.2645*** (0.0120)	0.2698*** (0.0120)	0.2657*** (0.0120)	0.2649*** (0.0120)
Borrower age	0.0012*** (0.0004)	0.0011** (0.0004)	0.0012*** (0.0004)	0.0011** (0.0004)	0.0011** (0.0004)
Education (low)	−0.0046 (0.0055)	−0.0019 (0.0055)	−0.0048 (0.0055)	−0.0023 (0.0055)	−0.0019 (0.0055)
Education (not reported)	−0.0101* (0.0052)	−0.0075 (0.0052)	−0.0106** (0.0052)	−0.0079 (0.0052)	−0.0075 (0.0052)
Gender (male)	−0.0213*** (0.0053)	−0.0165*** (0.0053)	−0.0213*** (0.0053)	−0.0162*** (0.0053)	−0.0165*** (0.0053)
Num of child	−0.0065 (0.0047)	−0.0059 (0.0047)	−0.0065 (0.0047)	−0.0057 (0.0047)	−0.0058 (0.0047)
Marriage (not married)	−0.0101* (0.0057)	−0.0094* (0.0057)	−0.0101* (0.0057)	−0.0097* (0.0057)	−0.0094 (0.0057)
Marriage (not reported)	−0.0271** (0.0127)	−0.0237* (0.0127)	−0.0286** (0.0127)	−0.0250** (0.0127)	−0.0233* (0.0127)
$Y \times$ Seasoned			0.0406*** (0.0041)		
$Y^s \times$ Seasoned				0.0415*** (0.0036)	
$Y^u \times$ Seasoned					−0.0063*** (0.0018)

Table 2 (continued)

	(1) Herding	(2) Decomposition	(3) Interaction I	(4) Interaction II	(5) Interaction III
Intercept	3.4004***	3.4432***	3.6462***	3.6738***	3.4161***
	(0.0404)	(0.0399)	(0.0475)	(0.0446)	(0.0406)
Day of week fixed effects	Yes	Yes	Yes	Yes	Yes
N	122,411	122,411	122,411	122,411	122,411
AIC	237,666.2011	237,355.6408	237,572.1660	237,223.7741	237,344.7327
BIC	237,977.0856	237,676.2404	237,892.7656	237,554.0889	237,675.0474
Log Likelihood	−118,801.1006	−118,644.8204	−118,753.0830	−118,577.8871	−118,638.3663

Y, Y^s and Y^u denote the log-transformed lending amount from all predecessors, seasoned predecessors, and unseasoned predecessors, respectively; *Day of Week* fixed effects capture the possibility that lending concentrates on certain days of a week; the base categories of purpose, education, gender, and marriage are described in Table 1; standard errors are presented in parentheses

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

5.2 Robustness checks

We perform a series of robustness checks in this section. We examine whether the findings in the previous section are robust with alternative measures of expertise and with alternative samples. We also account for serial correlation at the listing level, potential problems of endogeneity, and selection bias.

5.2.1 Alternative measure of "seasoned" investors

In the main analysis, we define investors as "seasoned" if their lender scores are among the top 10% (i.e., percentile = 0.90). As the definition of seasoned investors may influence the results of our analysis, we use an alternative measure of "seasoned" investor to check the robustness of the findings. First, we define an investor as "seasoned" if his/her lender score is among the top 5% (i.e., percentile = 0.95). The results, shown in Table 3, are consistent with the results in the main analysis. Next, we define an investor as "seasoned" if his/her lender score is among the top 15% (i.e., percentile = 0.85). The results, shown in Table 4, are also consistent with previous findings.

5.2.2 Alternative sample

As previously discussed in Sect. 4.1, we restrict our sample to listings that have received at least ten bids to ensure the possibility of herding. Next, we examine whether the findings are robust if we use all listings. The results, shown in Table 5, are largely consistent with the results in the main analysis.

In our research context, a small proportion of bids (6.9%) are made by algorithms that are predefined by investors. The decision-making process of such algorithm-based bids might be fundamentally different from that of bids made by humans, as the herding effect can hardly exist in nonhuman transactions. We thus re-estimate our model using a sample without these autobids. The results, reported in Table 6, are largely consistent with our main analysis.

5.2.3 First-order autoregression

We assume that there is no serial correlation among error terms in the main analysis. It is probable that error terms would be correlated with lagged independent variables, and such correlation would introduce bias into the estimation [28]. To address this potential issue, we thus fit multilevel models that allow for a first-order autoregressive correlation structure for residuals at the listing level. The results, presented in Table 7, are consistent with previous findings.

5.2.4 Potential problem of endogeneity

The estimation could be biased if the random intercepts in our multilevel models are correlated with the herding measure. The problem of endogeneity stems from such correlations. To address this potential issue, we fit models using multilevel

Table 3 Alternative measure of seasoned investors (top 5%)

	(1) Herding	(2) Decomposition	(3) Interaction I	(4) Interaction II	(5) Interaction III
Y: All predecessors	0.0463*** (0.0044)		0.0102* (0.0052)		
Y^s: Seasoned predecessors		0.0113*** (0.0023)		−0.0171*** (0.0029)	0.0113*** (0.0023)
Y^u: Unseasoned predecessors		−0.0159*** (0.0010)		−0.0167*** (0.0010)	−0.0155*** (0.0016)
Lag percent needed	0.1159*** (0.0206)	−0.1089*** (0.0172)	0.0927*** (0.0207)	−0.1107*** (0.0172)	−0.1085*** (0.0172)
Late fundraising stage	0.0214*** (0.0077)	−0.0061 (0.0076)	0.0214*** (0.0077)	−0.0036 (0.0076)	−0.0061 (0.0076)
Auto bid	0.3215*** (0.0090)	0.3065*** (0.0091)	0.3224*** (0.0090)	0.3049*** (0.0091)	0.3064*** (0.0091)
Time interval	−0.0098*** (0.0021)	−0.0103*** (0.0021)	−0.0111*** (0.0021)	−0.0112*** (0.0021)	−0.0103*** (0.0021)
Seasoned (1 = yes)	0.1014*** (0.0345)	0.0910*** (0.0346)	−0.2549*** (0.0445)	−0.2335*** (0.0403)	0.0947*** (0.0363)
Amount requested	0.1103*** (0.0057)	0.1606*** (0.0047)	0.1189*** (0.0057)	0.1633*** (0.0047)	0.1605*** (0.0047)
Interest rate	−0.0028*** (0.0006)	−0.0027*** (0.0006)	−0.0028*** (0.0006)	−0.0027*** (0.0006)	−0.0027*** (0.0006)
Loan duration	−0.0013** (0.0007)	−0.0029*** (0.0007)	−0.0013** (0.0007)	−0.0028*** (0.0007)	−0.0029*** (0.0007)
Credit risky	−0.0153*** (0.0051)	−0.0136*** (0.0051)	−0.0170*** (0.0051)	−0.0155*** (0.0051)	−0.0136*** (0.0051)
Title length	−0.0023*** (0.0003)	−0.0021*** (0.0003)	−0.0023*** (0.0003)	−0.0020*** (0.0003)	−0.0021*** (0.0003)
Purpose (enterprise startup)	0.0093 (0.0067)	0.0110 (0.0067)	0.0087 (0.0067)	0.0106 (0.0067)	0.0110 (0.0067)

Table 3 (continued)

	(1) Herding	(2) Decomposition	(3) Interaction I	(4) Interaction II	(5) Interaction III
Purpose (other purpose)	0.0259*** (0.0064)	0.0255*** (0.0064)	0.0260*** (0.0064)	0.0264*** (0.0064)	0.0255*** (0.0064)
Purpose (short-term turnover debt)	0.0030 (0.0046)	0.0025 (0.0046)	0.0027 (0.0046)	0.0024 (0.0046)	0.0025 (0.0046)
Purpose (not reported)	0.2690*** (0.0120)	0.2648*** (0.0120)	0.2711*** (0.0120)	0.2673*** (0.0120)	0.2648*** (0.0120)
Borrower age	0.0012*** (0.0004)	0.0010** (0.0004)	0.0012*** (0.0004)	0.0011** (0.0004)	0.0010** (0.0004)
Education (low)	−0.0047 (0.0055)	−0.0023 (0.0055)	−0.0051 (0.0055)	−0.0034 (0.0055)	−0.0023 (0.0055)
Education (not reported)	−0.0101* (0.0052)	−0.0093* (0.0052)	−0.0105** (0.0052)	−0.0098* (0.0052)	−0.0093* (0.0052)
Gender (male)	−0.0213*** (0.0053)	−0.0196*** (0.0053)	−0.0214*** (0.0053)	−0.0197*** (0.0053)	−0.0196*** (0.0053)
Num of child	−0.0066 (0.0047)	−0.0070 (0.0047)	−0.0064 (0.0047)	−0.0067 (0.0047)	−0.0070 (0.0047)
Marriage (not married)	−0.0101* (0.0057)	−0.0110* (0.0057)	−0.0100* (0.0057)	−0.0112** (0.0057)	−0.0110* (0.0057)
Marriage (not reported)	−0.0271** (0.0127)	−0.0255** (0.0127)	−0.0292** (0.0127)	−0.0277** (0.0127)	−0.0254** (0.0127)
$Y\times$ Seasoned			0.0453*** (0.0036)		
$Y^s\times$ Seasoned				0.0447*** (0.0028)	
$Y^u\times$ Seasoned					−0.0006 (0.0017)

Table 3 (continued)

	(1) Herding	(2) Decomposition	(3) Interaction I	(4) Interaction II	(5) Interaction III
Intercept	3.4125*** (0.0402)	3.4847*** (0.0397)	3.6326*** (0.0438)	3.6717*** (0.0414)	3.4825*** (0.0403)
Day of week fixed effects	Yes	Yes	Yes	Yes	Yes
N	122,411	122,411	122,411	122,411	122,411
AIC	237,677.2676	237,504.3779	237,520.2465	237,260.7256	237,506.2656
BIC	237,988.1521	237,824.9775	237,840.8461	237,591.0404	237,836.5803
Log Likelihood	−118,806.6338	−118,719.1890	−118,727.1232	−118,596.3628	−118,719.1328

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

Table 4 Alternative measure of seasoned investors (top 15%)

	(1) Herding	(2) Decomposition	(3) Interaction I	(4) Interaction II	(5) Interaction III
Y: All predecessors	0.0462*** (0.0044)		0.0122* (0.0063)		
Y^s: Seasoned predecessors		0.0246*** (0.0033)		−0.0080 (0.0050)	0.0252*** (0.0033)
Y^u: Unseasoned predecessors		−0.0142*** (0.0009)		−0.0144*** (0.0009)	−0.0084*** (0.0018)
Lag percent needed	0.1158*** (0.0206)	−0.0445** (0.0187)	0.1057*** (0.0206)	−0.0465** (0.0187)	−0.0425** (0.0187)
Late fundraising stage	0.0215*** (0.0077)	0.0081 (0.0076)	0.0214*** (0.0077)	0.0091 (0.0076)	0.0081 (0.0076)
Auto bid	0.3210*** (0.0090)	0.3053*** (0.0091)	0.3209*** (0.0090)	0.3047*** (0.0091)	0.3045*** (0.0091)
Time interval	−0.0098*** (0.0021)	−0.0099*** (0.0021)	−0.0103*** (0.0021)	−0.0103*** (0.0021)	−0.0096*** (0.0021)
Seasoned (1 = yes)	0.1510*** (0.0230)	0.1419*** (0.0230)	−0.1365*** (0.0446)	−0.1463*** (0.0403)	0.1776*** (0.0251)
Amount requested	0.1104*** (0.0057)	0.1467*** (0.0051)	0.1139*** (0.0057)	0.1480*** (0.0051)	0.1459*** (0.0051)
Interest rate	−0.0029*** (0.0006)	−0.0030*** (0.0006)	−0.0028*** (0.0006)	−0.0029*** (0.0006)	−0.0030*** (0.0006)
Loan duration	−0.0014** (0.0007)	−0.0038*** (0.0007)	−0.0014** (0.0007)	−0.0037*** (0.0007)	−0.0038*** (0.0007)
Credit risky	−0.0153*** (0.0051)	−0.0135*** (0.0051)	−0.0161*** (0.0051)	−0.0143*** (0.0051)	−0.0133*** (0.0051)
Title length	−0.0023*** (0.0003)	−0.0021*** (0.0003)	−0.0023*** (0.0003)	−0.0020*** (0.0003)	−0.0021*** (0.0003)
Purpose (enterprise startup)	0.0093 (0.0067)	0.0124* (0.0067)	0.0093 (0.0067)	0.0122* (0.0067)	0.0124* (0.0067)

Table 4 (continued)

	(1) Herding	(2) Decomposition	(3) Interaction I	(4) Interaction II	(5) Interaction III
Purpose (other purpose)	0.0259***	0.0261***	0.0260***	0.0265***	0.0262***
	(0.0064)	(0.0064)	(0.0064)	(0.0064)	(0.0064)
Purpose (short-term turnover debt)	0.0030	0.0024	0.0030	0.0026	0.0024
	(0.0046)	(0.0046)	(0.0046)	(0.0046)	(0.0046)
Purpose (not reported)	0.2688***	0.2634***	0.2691***	0.2642***	0.2639***
	(0.0120)	(0.0120)	(0.0120)	(0.0120)	(0.0120)
Borrower age	0.0012***	0.0011**	0.0012***	0.0011**	0.0011**
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Education (low)	−0.0046	−0.0008	−0.0048	−0.0011	−0.0008
	(0.0055)	(0.0055)	(0.0055)	(0.0055)	(0.0055)
Education (not reported)	−0.0101*	−0.0071	−0.0104**	−0.0074	−0.0071
	(0.0052)	(0.0052)	(0.0052)	(0.0052)	(0.0052)
Gender (male)	−0.0213***	−0.0177***	−0.0212***	−0.0176***	−0.0177***
	(0.0053)	(0.0053)	(0.0053)	(0.0053)	(0.0053)
Num of child	−0.0066	−0.0060	−0.0065	−0.0059	−0.0060
	(0.0047)	(0.0047)	(0.0047)	(0.0047)	(0.0047)
Marriage (not married)	−0.0101*	−0.0092	−0.0102*	−0.0093	−0.0091
	(0.0057)	(0.0057)	(0.0057)	(0.0057)	(0.0057)
Marriage (not reported)	−0.0271**	−0.0211*	−0.0282**	−0.0221*	−0.0205
	(0.0127)	(0.0127)	(0.0127)	(0.0127)	(0.0127)
$Y \times Seasoned$			0.0364***		
			(0.0048)		
$Y^s \times Seasoned$				0.0377***	
				(0.0043)	
$Y^u \times Seasoned$					−0.0068***
					(0.0019)

Table 4 (continued)

	(1) Herding	(2) Decomposition	(3) Interaction I	(4) Interaction II	(5) Interaction III
Intercept	3.3811***	3.4053***	3.6233***	3.6426***	3.3757***
	(0.0406)	(0.0402)	(0.0518)	(0.0485)	(0.0410)
Day of week fixed effects	Yes	Yes	Yes	Yes	Yes
N	122,411	122,411	122,411	122,411	122,411
AIC	237,642.8885	237,374.7152	237,588.3852	237,301.1407	237,364.0243
BIC	237,953.7729	237,695.3148	237,908.9848	237,631.4554	237,694.3390
Log Likelihood	−118,789.4442	−118,654.3576	−118,761.1926	−118,616.5703	−118,648.0121

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 5 Alternative listing sample (using all listings)

	(1) Herding	(2) Decomposition	(3) Interaction I	(4) Interaction II	(5) Interaction III
Y: All predecessors	0.0662***		0.0336***		
	(0.0041)		(0.0054)		
Y^s : Seasoned predecessors		0.0276***		−0.0060	0.0285***
		(0.0027)		(0.0038)	(0.0027)
Y^u: Unseasoned predecessors		−0.0199***		−0.0203***	−0.0119***
		(0.0009)		(0.0009)	(0.0016)
Lag percent needed	0.1653***	−0.1085***	0.1516***	−0.1105***	−0.1041***
	(0.0203)	(0.0179)	(0.0204)	(0.0179)	(0.0179)
Late fundraising stage	0.0205***	−0.0110	0.0205***	−0.0089	−0.0109
	(0.0078)	(0.0076)	(0.0078)	(0.0076)	(0.0076)
Auto bid	0.3072***	0.2844***	0.3074***	0.2833***	0.2827***
	(0.0090)	(0.0090)	(0.0090)	(0.0090)	(0.0090)
Time interval	−0.0107***	−0.0171***	−0.0113***	−0.0173***	−0.0166***
	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)
Seasoned (1 = yes)	0.1275***	0.1133***	−0.1560***	−0.2014***	0.1693***
	(0.0262)	(0.0263)	(0.0401)	(0.0365)	(0.0280)
Log amount requested	0.0777***	0.1366***	0.0824***	0.1384***	0.1352***
	(0.0055)	(0.0048)	(0.0055)	(0.0048)	(0.0048)
Interest rate	−0.0029***	−0.0030***	−0.0029***	−0.0030***	−0.0031***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Loan duration	0.0003	−0.0027***	0.0003	−0.0026***	−0.0027***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Credit risky	−0.0331***	−0.0326***	−0.0339***	−0.0333***	−0.0322***
	(0.0050)	(0.0050)	(0.0050)	(0.0050)	(0.0050)
Title length	−0.0025***	−0.0021***	−0.0025***	−0.0021***	−0.0021***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Purpose (enterprise startup)	0.0057	0.0091	0.0056	0.0089	0.0092
	(0.0067)	(0.0066)	(0.0066)	(0.0066)	(0.0066)

Table 5 (continued)

	(1) Herding	(2) Decomposition	(3) Interaction I	(4) Interaction II	(5) Interaction III
Purpose (other purpose)	0.0165*** (0.0063)	0.0169*** (0.0063)	0.0167*** (0.0063)	0.0174*** (0.0063)	0.0171*** (0.0063)
Purpose (short-term turnover debt)	0.0041 (0.0046)	0.0043 (0.0045)	0.0041 (0.0046)	0.0044 (0.0045)	0.0044 (0.0045)
Purpose (not reported)	0.2684*** (0.0121)	0.2607*** (0.0121)	0.2692*** (0.0121)	0.2622*** (0.0121)	0.2614*** (0.0121)
Borrower age	0.0017*** (0.0004)	0.0015*** (0.0004)	0.0017*** (0.0004)	0.0015*** (0.0004)	0.0015*** (0.0004)
Education (low)	−0.0043 (0.0054)	−0.0013 (0.0054)	−0.0044 (0.0054)	−0.0016 (0.0054)	−0.0014 (0.0054)
Education (not reported)	−0.0151*** (0.0051)	−0.0120** (0.0051)	−0.0155*** (0.0051)	−0.0124** (0.0051)	−0.0119** (0.0051)
Gender (male)	−0.0240*** (0.0053)	−0.0187*** (0.0052)	−0.0239*** (0.0053)	−0.0185*** (0.0052)	−0.0187*** (0.0052)
Num of child	−0.0076 (0.0046)	−0.0069 (0.0046)	−0.0076 (0.0046)	−0.0068 (0.0046)	−0.0068 (0.0046)
Marriage (not married)	−0.0136** (0.0056)	−0.0126** (0.0056)	−0.0137** (0.0056)	−0.0129** (0.0056)	−0.0126** (0.0056)
Marriage (not reported)	−0.0339*** (0.0126)	−0.0285** (0.0126)	−0.0353*** (0.0126)	−0.0300** (0.0126)	−0.0277** (0.0126)
Y × *Seasoned*			0.0362*** (0.0039)		
Y^s × *Seasoned*				0.0422*** (0.0034)	
Y^u × *Seasoned*					−0.0099*** (0.0017)

Table 5 (continued)

	(1) Herding	(2) Decomposition	(3) Interaction I	(4) Interaction II	(5) Interaction III
Intercept	3.5031***	3.5711***	3.7227***	3.8061***	3.5289***
	(0.0402)	(0.0397)	(0.0466)	(0.0440)	(0.0404)
Day of week fixed effects	Yes	Yes	Yes	Yes	Yes
N	130,973	130,973	130,973	130,973	130,973
AIC	259,620.4848	259,191.6894	259,536.0486	259,041.1172	259,158.7774
BIC	259,933.5326	259,514.5200	259,858.8793	259,373.7306	259,491.3907
Log Likelihood	−129,778.2424	−129,562.8447	−129,735.0243	−129,486.5586	−129,545.3887

$^{**}p < 0.05$, $^{***}p < 0.01$

Table 6 Alternative sample (without auto bids)

	(1) Herding	(2) Decomposition	(3) Interaction I	(4) Interaction II	(5) Interaction III
Y: All predecessors	0.0463***		0.0081		
	(0.0047)		(0.0060)		
Y^s: Seasoned predecessors		0.0191***		−0.0144***	0.0197***
		(0.0030)		(0.0042)	(0.0030)
Y^u: UnSeasoned predecessors		−0.0183***		−0.0187***	−0.0130***
		(0.0010)		(0.0010)	(0.0018)
Lag percent needed	0.1107***	−0.0982***	0.0951***	−0.0997***	−0.0954***
	(0.0218)	(0.0190)	(0.0218)	(0.0190)	(0.0191)
Late fundraising stage	0.0179**	−0.0024	0.0179**	−0.0006	−0.0024
	(0.0081)	(0.0080)	(0.0081)	(0.0080)	(0.0080)
Auto bid	0.0000	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)	(.)
Time interval	−0.0108***	−0.0114***	−0.0116***	−0.0121***	−0.0111***
	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)
Seasoned (1 = yes)	0.1223***	0.1111***	−0.2201***	−0.2154***	0.1497***
	(0.0271)	(0.0272)	(0.0436)	(0.0390)	(0.0293)
Amount requested	0.1227***	0.1684***	0.1283***	0.1699***	0.1672***
	(0.0061)	(0.0053)	(0.0061)	(0.0053)	(0.0053)
Interest rate	−0.0032***	−0.0031***	−0.0032***	−0.0031***	−0.0031***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Loan duration	−0.0021***	−0.0046***	−0.0020***	−0.0046***	−0.0046***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Credit risky	−0.0086	−0.0057	−0.0097*	−0.0067	−0.0055
	(0.0054)	(0.0053)	(0.0054)	(0.0053)	(0.0053)
Title length	−0.0024***	−0.0021***	−0.0023***	−0.0021***	−0.0021***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Purpose (enterprise startup)	0.0148**	0.0176**	0.0148**	0.0176**	0.0176**
	(0.0072)	(0.0072)	(0.0072)	(0.0072)	(0.0072)

Table 6 (continued)

	(1) Herding	(2) Decomposition	(3) Interaction I	(4) Interaction II	(5) Interaction III
Purpose (other purpose)	0.0259*** (0.0069)	0.0260*** (0.0069)	0.0262*** (0.0069)	0.0267*** (0.0069)	0.0261*** (0.0069)
Purpose (short-term turnover debt)	0.0028 (0.0049)	0.0026 (0.0049)	0.0028 (0.0049)	0.0029 (0.0049)	0.0027 (0.0049)
Purpose (not reported)	0.2831*** (0.0125)	0.2780*** (0.0124)	0.2839*** (0.0124)	0.2791*** (0.0124)	0.2785*** (0.0124)
Borrower age	0.0013*** (0.0004)	0.0011** (0.0004)	0.0013*** (0.0004)	0.0011** (0.0004)	0.0011** (0.0004)
Education (low)	−0.0053 (0.0058)	−0.0020 (0.0058)	−0.0054 (0.0058)	−0.0024 (0.0058)	−0.0020 (0.0058)
Education (not reported)	−0.0142*** (0.0055)	−0.0109** (0.0055)	−0.0147*** (0.0055)	−0.0113** (0.0055)	−0.0109** (0.0055)
Gender (male)	−0.0248*** (0.0056)	−0.0194*** (0.0056)	−0.0248*** (0.0056)	−0.0191*** (0.0056)	−0.0193*** (0.0056)
Num of child	−0.0068 (0.0050)	−0.0060 (0.0050)	−0.0067 (0.0050)	−0.0058 (0.0050)	−0.0059 (0.0050)
Marriage (not married)	−0.0119** (0.0061)	−0.0111* (0.0060)	−0.0120** (0.0061)	−0.0113* (0.0060)	−0.0110* (0.0060)
Marriage (not reported)	−0.0198 (0.0137)	−0.0170 (0.0137)	−0.0215 (0.0137)	−0.0186 (0.0137)	−0.0166 (0.0137)
$Y \times Seasoned$			0.0433*** (0.0043)		
$Y^s \times Seasoned$				0.0434*** (0.0037)	
$Y^u \times Seasoned$					−0.0066*** (0.0019)

Table 6 (continued)

	(1) Herding	(2) Decomposition	(3) Interaction I	(4) Interaction II	(5) Interaction III
Intercept	3.3088***	3.3517***	3.5674***	3.5903***	3.3238***
	(0.0431)	(0.0426)	(0.0502)	(0.0473)	(0.0433)
Day of week fixed effects	Yes	Yes	Yes	Yes	Yes
N	112,881	112,881	112,881	112,881	112,881
AIC	224,040.2503	223,716.5313	223,942.1833	223,583.6734	223,705.9498
BIC	224,338.9070	224,024.8222	224,250.4742	223,901.5984	224,023.8747
Log Likelihood	−111,989.1251	−111,826.2657	−111,939.0917	−111,758.8367	−111,819.9749

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

Table 7 First-order autoregression

	(1) Herding	(2) Decomposition	(3) Interaction I	(4) Interaction II	(5) Interaction III
Y: All predecessors	0.0278*** (0.0055)		0.0095 (0.0058)		
Y^s: Seasoned predecessors		0.0131*** (0.0037)		−0.0222*** (0.0051)	0.0198*** (0.0029)
Y^u: Unseasoned predecessors		−0.0089*** (0.0013)		−0.0095*** (0.0013)	−0.0116*** (0.0017)
Lag percent needed	0.2077*** (0.0257)	0.0951*** (0.0229)	0.1009*** (0.0208)	0.0856*** (0.0229)	−0.0799*** (0.0181)
Late fundraising stage	0.0426*** (0.0096)	0.0320*** (0.0095)	0.0211*** (0.0077)	0.0333*** (0.0095)	0.0014 (0.0076)
Auto bid	0.5387*** (0.0101)	0.5308*** (0.0101)	0.3270*** (0.0091)	0.5313*** (0.0101)	0.3053*** (0.0092)
Time interval	−0.0067*** (0.0026)	−0.0071*** (0.0026)	−0.0103*** (0.0021)	−0.0078*** (0.0026)	−0.0094*** (0.0020)
Seasoned (1 = yes)	0.0127** (0.0054)	0.0094* (0.0054)	−0.2026*** (0.0420)	−0.3119*** (0.0324)	0.1418*** (0.0282)
Amount requested	0.1337*** (0.0093)	0.1556*** (0.0084)	0.1169*** (0.0057)	0.1586*** (0.0084)	0.1542*** (0.0049)
Interest rate	0.0096*** (0.0010)	0.0097*** (0.0010)	−0.0028*** (0.0006)	0.0097*** (0.0010)	−0.0030*** (0.0006)
Loan duration	0.0008 (0.0012)	−0.0006 (0.0012)	−0.0014** (0.0007)	−0.0002 (0.0012)	−0.0038*** (0.0007)
Credit risky	−0.0224** (0.0090)	−0.0201** (0.0088)	−0.0160*** (0.0051)	−0.0216** (0.0088)	−0.0117** (0.0051)
Title length	−0.0029*** (0.0006)	−0.0027*** (0.0006)	−0.0023*** (0.0003)	−0.0027*** (0.0006)	−0.0020*** (0.0003)
Purpose (enterprise startup)	0.0085 (0.0127)	0.0101 (0.0124)	0.0099 (0.0067)	0.0098 (0.0123)	0.0131* (0.0067)

Table 7 (continued)

	(1) Herding	(2) Decomposition	(3) Interaction I	(4) Interaction II	(5) Interaction III
Purpose (other purpose)	0.0305*** (0.0118)	0.0291** (0.0116)	0.0261*** (0.0064)	0.0294** (0.0115)	0.0266*** (0.0064)
Purpose (short-term turnover debt)	0.0117 (0.0085)	0.0117 (0.0083)	0.0029 (0.0046)	0.0117 (0.0082)	0.0032 (0.0046)
Purpose (not reported)	0.2697*** (0.0220)	0.2630*** (0.0215)	0.2689*** (0.0120)	0.2651*** (0.0213)	0.2641*** (0.0120)
Borrower age	0.0009 (0.0008)	0.0008 (0.0008)	0.0012*** (0.0004)	0.0008 (0.0008)	0.0011** (0.0004)
Education (low)	0.0018 (0.0101)	0.0043 (0.0099)	−0.0045 (0.0055)	0.0034 (0.0098)	−0.0016 (0.0055)
Education (not reported)	0.0169* (0.0088)	0.0203** (0.0086)	−0.0107** (0.0052)	0.0196** (0.0085)	−0.0076 (0.0052)
Gender (male)	−0.0342*** (0.0097)	−0.0317*** (0.0095)	−0.0213*** (0.0053)	−0.0316*** (0.0094)	−0.0164*** (0.0053)
Num of child	−0.0185** (0.0088)	−0.0175** (0.0086)	−0.0062 (0.0047)	−0.0171** (0.0085)	−0.0055 (0.0047)
Marriage (not married)	−0.0226** (0.0106)	−0.0220** (0.0104)	−0.0098* (0.0057)	−0.0222** (0.0103)	−0.0090 (0.0057)
Marriage (not reported)	−0.0117 (0.0242)	−0.0093 (0.0237)	−0.0287** (0.0127)	−0.0107 (0.0235)	−0.0233* (0.0127)
$Y \times Seasoned$			0.0403*** (0.0042)		
$Y^s \times Seasoned$				0.0432*** (0.0043)	
$Y^u \times Seasoned$					−0.0064*** (0.0018)

Table 7 (continued)

	(1) Herding	(2) Decomposition	(3) Interaction I	(4) Interaction II	(5) Interaction III
Intercept	3.2387***	3.2743***	3.6396***	3.5153***	3.4095***
	(0.0734)	(0.0714)	(0.0476)	(0.0747)	(0.0406)
Day of week fixed effects	Yes	Yes	Yes	Yes	Yes
N	122,411	122,411	122,411	122,411	122,411
AIC	286,312.0935	286,276.5448	236,981.2100	286,177.4158	236,744.7293
BIC	286,632.6931	286,606.8595	237,311.5248	286,517.4456	237,084.7592
Log Likelihood	−143,123.0468	−143,104.2724	−118,456.6050	−143,053.7079	−118,337.3647

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

generalized method of moments (GMM) estimators [30]. The results, shown in Table 8, are consistent with previous findings.

5.2.5 Potential problem of selection bias

In the main analysis, we do not consider individuals who do not participate in lending. A potential problem of selection bias may occur if factors that affect an investor's choice of which listing to participate in also affect the investor's decision of how much to lend [28]. We address this concern by using a two-step Heckman correction procedure suggested by Liu et al. [36] and Jiang et al. [28]. First, we run a probit model estimating the probability of an investor's participation in bidding on a listing. We construct the investor's consideration set using all listings that are open for auction by the time he/she makes a bid. From this probit model, we calculate the inverse Mills ratio. Then, we include the inverse Mills ratio in the main model to correct the potential problem of selection bias. The estimation results from the first step probit model are shown in "Appendix A". The results of the selection bias corrected model, presented in Table 9, are consistent with previous findings.

5.3 Additional analysis

We conduct additional analyses to further understand the role of investment expertise in predicting loan performance. We examine whether loans that receive a greater lending amount from seasoned and unseasoned investors have better loan performance. Among the 4372 listings in our dataset, 1762 are successfully funded and have turned into loans. The analysis in this section is based on such loans. According to the consumer finance literature, we label a loan as *Late* if the payment of a loan is late for 30 or more days and *Defaulted* if the repayment is late for 90 or more days [22]. The descriptive analysis of this dataset is shown in "Appendix B". Some loans in the sample had not reached their maturity when the loan performance data were collected, which may cause the problem of right censoring. We thus estimated a Cox proportional hazards (CPH) model of loan late rates and a CPH model of default rates. The CPH model, widely accepted in studying loan performances [15], relates the time that passes before an event (i.e., late or default) occurs (if any) to loan covariates. The Kaplan–Meier approach was used to fit the empirical hazard rates. We also estimated a probit model and a logit model to examine whether the results are robust among different estimators.

Table 10 presents the association between loan attributes and late rates. The association between the late rate and the logarithm of the total lending amount (Y^s) from seasoned investors is negative and statistically significant, implying that hidden talent in seasoned investors is valuable in predicting the loan performance of the late rate. However, the association between the late rate and the logarithm of the total lending amount (Y^u) from unseasoned investors is not significant, implying that the herding signal from unseasoned investors is not informative in the current research context.

Table 8 Multilevel GMM

	(1) Herding	(2) Decomposition	(3) Interaction I	(4) Interaction II	(5) Interaction III
Y: All predecessors	0.051*** (0.004)		0.013* (0.006)		
Y^s: Seasoned predecessors		0.020*** (0.003)		−0.015*** (0.004)	0.021*** (0.003)
Y^u: Unseasoned predecessors		−0.018*** (0.001)		−0.019*** (0.001)	−0.012*** (0.002)
Lag percent needed	0.104*** (0.021)	0.0120*** (0.018)	0.088*** (0.021)	−0.121*** (0.018)	−0.116*** (0.018)
Late fundraising stage	0.016* (0.008)	−0.007 (0.008)	0.016* (0.007)	−0.005 (0.008)	−0.006 (0.008)
Auto bid	0.320*** (0.009)	0.297*** (0.009)	0.321*** (0.009)	0.296*** (0.009)	0.296*** (0.009)
Time interval	−0.009*** (0.002)	−0.009*** (0.002)	−0.010*** (0.002)	−0.010*** (0.002)	−0.009*** (0.002)
Seasoned (1 = yes)	0.125*** (0.026)	0.112*** (0.026)	−0.210*** (0.042)	−0.224*** (0.038)	0.155*** (0.028)
Amount requested	0.112*** (0.006)	0.162*** (0.005)	0.117*** (0.006)	0.162*** (0.005)	0.160*** (0.005)
Interest rate	−0.003*** (0.001)	−0.004*** (0.001)	−0.003*** (0.001)	−0.004*** (0.001)	−0.004*** (0.001)
Loan duration	−0.002* (0.001)	−0.004*** (0.001)	−0.002*** (0.001)	−0.004*** (0.001)	−0.004*** (0.001)
Credit risky	−0.011* (0.005)	−0.007 (0.005)	−0.011 (0.005)	−0.009 (0.005)	−0.007 (0.005)
Title length	−0.002*** (0.000)	−0.002*** (0.000)	−0.002*** (0.000)	−0.002*** (0.000)	−0.002*** (0)
Purpose (enterprise startup)	0.009 (0.007)	0.013 (0.007)	0.010 (0.007)	0.013* (0.007)	0.013* (0.007)
Purpose (other purpose)	0.026*** (0.006)	0.027*** (0.006)	0.026*** (0.006)	0.027*** (0.006)	0.027*** (0.006)
Purpose (short-term turnover debt)	0.001 (0.005)	0.002 (0.005)	0.001 (0.004)	0.002 (0.004)	0.002 (0.005)
Purpose (not reported)	0.276*** (0.011)	0.272*** (0.011)	0.277*** (0.011)	0.272*** (0.011)	0.272*** (0.011)
Borrower age	0.001** (0.000)	0.001** (0.000)	0.001** (0.000)	0.001** (0.000)	0.001** (0)
Education (low)	−0.005 (0.005)	−0.002 (0.005)	−0.005 (0.005)	−0.002 (0.005)	−0.002 (0.005)
Education (not reported)	−0.008 (0.005)	−0.004 (0.005)	−0.008 (0.005)	−0.005 (0.005)	−0.004 (0.005)
Gender (male)	−0.023*** (0.005)	−0.018*** (0.005)	−0.023*** (0.005)	−0.017*** (0.005)	−0.018*** (0.005)
Num of child	−0.007 (0.005)	−0.007 (0.005)	−0.007 (0.005)	−0.007 (0.005)	−0.007 (0.005)
Marriage (not married)	−0.011* (0.006)	−0.010* (0.006)	−0.011* (0.006)	−0.010* (0.006)	−0.010* (0.006)

Table 8 (continued)

	(1) Herding	(2) Decomposition	(3) Interaction I	(4) Interaction II	(5) Interaction III
Marriage (not reported)	−0.019 (0.012)	−0.016 (0.012)	−0.021 (0.012)	−0.017 (0.012)	−0.015 (0.012)
$Y \times Seasoned$			0.042*** (0.004)		
$Y^s \times Seasoned$				0.045*** (0.004)	
$Y^u \times Seasoned$					−0.007*** (0.002)
Intercept	3.374*** (0.039)	3.422*** (0.038)	3.635*** (0.047)	3.676*** (0.044)	3.390*** (0.040)
Day of week fixed effects	Yes	Yes	Yes	Yes	Yes
N	122,411	122,411	122,411	122,411	122,411

$^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 11 presents the association between loan attributes and default rates. The coefficient of Y^s is negative across the three estimation models and statistically significant in the probit and logit models, while the coefficient of Y^u is not significant across the three estimation models. Such findings also show that seasoned investors' lending amount is a useful signal in predicting loan performance, while unseasoned investors' lending amount is not.

6 Discussions

6.1 Main findings

This study investigates the role of expertise in herding behaviors in China's online debt-based crowdfunding market. We divide investors into two categories: seasoned investors and unseasoned investors. We examine (1) whether seasoned investors are more influential than unseasoned investors in attracting lending amounts and (2) whether seasoned and unseasoned investors behave differently toward the same herding signal. The main findings are summarized below, and the implications for research and practices follow.

First, our results reveal that seasoned investors are more influential than unseasoned investors. Listings with greater lending amounts from expert predecessors will attract more lending amounts from successors. The findings are consistent with the views that individuals weigh advice more heavily when advisors are more experienced or knowledgeable. Such findings imply that seasoned investors play a critical role in the crowdfunding market. Investors differentiate signals from seasoned and unseasoned predecessors, hoping to extract more useful information.

Second, our results reveal that investors with different expertise levels respond differently to market signals. Contrary to our expectations, seasoned investors are

Table 9 Heckman correction of selection bias

	(1) Herding	(2) Decomposition	(3) Interaction I	(4) Interaction II	(5) Interaction III
Y: All predecessors	0.0460*** (0.0044)		0.0073 (0.0054)		
Y^s : Seasoned predecessors		0.0161*** (0.0025)		−0.0163*** (0.0033)	0.0163*** (0.0025)
Y^u : Unseasoned predecessors		−0.0163*** (0.0010)		−0.0171*** (0.0010)	−0.0147*** (0.0016)
Lag percent needed	0.1157*** (0.0206)	−0.0950*** (0.0175)	0.0935*** (0.0207)	−0.0979*** (0.0175)	−0.0936*** (0.0175)
Late fundraising stage	0.0212*** (0.0077)	−0.0032 (0.0076)	0.0210*** (0.0077)	−0.0010 (0.0076)	−0.0032 (0.0076)
Auto bid	0.3221*** (0.0090)	0.3038*** (0.0091)	0.3232*** (0.0090)	0.3025*** (0.0091)	0.3034*** (0.0091)
Time interval	−0.0095*** (0.0019)	−0.0095*** (0.0019)	−0.0106*** (0.0019)	−0.0104*** (0.0019)	−0.0094*** (0.0019)
Seasoned (1 = yes)	0.0496 (0.0315)	0.0399 (0.0316)	−0.3164*** (0.0431)	−0.3064*** (0.0388)	0.0529 (0.0333)
Amount requested	1.4771*** (0.1739)	1.4879*** (0.1736)	1.5163*** (0.1738)	1.5262*** (0.1734)	1.4867*** (0.1736)
Interest rate	0.0533*** (0.0072)	0.0521*** (0.0072)	0.0546*** (0.0072)	0.0535*** (0.0072)	0.0521*** (0.0072)
Loan duration	−0.1487*** (0.0187)	−0.1468*** (0.0187)	−0.1520*** (0.0187)	−0.1506*** (0.0187)	−0.1468*** (0.0187)
Credit risky	−1.4800*** (0.1863)	−1.4410*** (0.1861)	−1.5149*** (0.1862)	−1.4810*** (0.1859)	−1.4402*** (0.1861)
Title length	−0.0038*** (0.0004)	−0.0035*** (0.0004)	−0.0038*** (0.0004)	−0.0035*** (0.0004)	−0.0035*** (0.0004)
Purpose (enterprise startup)	0.2847*** (0.0357)	0.2802*** (0.0356)	0.2905*** (0.0356)	0.2871*** (0.0356)	0.2801*** (0.0356)

Table 9 (continued)

	(1) Herding	(2) Decomposition	(3) Interaction I	(4) Interaction II	(5) Interaction III
Purpose (other purpose)	0.5354*** (0.0651)	0.5226*** (0.0650)	0.5471*** (0.0651)	0.5367*** (0.0650)	0.5224*** (0.0650)
Purpose (short-term turnover debt)	0.1997*** (0.0254)	0.1942*** (0.0254)	0.2040*** (0.0254)	0.1995*** (0.0254)	0.1941*** (0.0254)
Purpose (not reported)	2.6067*** (0.2975)	2.5440*** (0.2971)	2.6615*** (0.2974)	2.6073*** (0.2968)	2.5428*** (0.2971)
Borrower age	0.0054*** (0.0007)	0.0050*** (0.0007)	0.0055*** (0.0007)	0.0051*** (0.0007)	0.0050*** (0.0007)
Education (low)	−0.4614*** (0.0583)	−0.4481*** (0.0583)	−0.4720*** (0.0583)	−0.4609*** (0.0582)	−0.4479*** (0.0583)
Education (not reported)	−1.3035*** (0.1646)	−1.2698*** (0.1643)	−1.3330*** (0.1645)	−1.3038*** (0.1642)	−1.2692*** (0.1643)
Gender (male)	−0.4285*** (0.0521)	−0.4150*** (0.0520)	−0.4379*** (0.0520)	−0.4256*** (0.0519)	−0.4148*** (0.0520)
Num of child	−0.0361*** (0.0060)	−0.0353*** (0.0060)	−0.0367*** (0.0060)	−0.0359*** (0.0060)	−0.0353*** (0.0060)
Marriage (not married)	−0.0884*** (0.0115)	−0.0873*** (0.0115)	−0.0901*** (0.0115)	−0.0893*** (0.0115)	−0.0872*** (0.0115)
Marriage (not reported)	−0.6046*** (0.0745)	−0.5882*** (0.0744)	−0.6196*** (0.0745)	−0.6050*** (0.0744)	−0.5877*** (0.0744)
λ : *Inverse Mills Ratio*	5.7775*** (0.7347)	5.6302*** (0.7337)	5.9087*** (0.7343)	5.7808*** (0.7330)	5.6270*** (0.7337)
$Y \times Seasoned$			0.0463*** (0.0037)		
$Y^s \times Seasoned$				0.0469*** (0.0031)	

Table 9 (continued)

	(1) Herding	(2) Decomposition	(3) Interaction I	(4) Interaction II	(5) Interaction III
$Y^u \times Seasoned$					−0.0021 (0.0017)
Intercept	−21.1315*** (3.1212)	−20.4394*** (3.1170)	−21.4439*** (3.1193)	−20.8596*** (3.1137)	−20.4343*** (3.1169)
Day of week fixed effects	Yes	Yes	Yes	Yes	Yes
N	122,411	122,411	122,411	122,411	122,411
AIC	237,616.7686	237,380.6505	237,464.1076	237,149.2371	237,381.1619
BIC	237,937.3682	237,710.9653	237,794.4224	237,489.2670	237,721.1918
Log Likelihood	−118,775.3843	−118,656.3253	−118,698.0538	−118,539.6185	−118,655.5810

***$p < 0.01$

Table 10 Herding and late rates

	(1) Cox CPH	(2) Logit	(3) Probit
Y^s : Amount from seasoned	−0.4017**	−0.3136*	−0.1647*
	(0.1585)	(0.1703)	(0.0863)
Y^u : Amount from unseasoned	−0.0254	0.0418	0.0164
	(0.0619)	(0.0686)	(0.0326)
interest rate	0.1844***	0.1887***	0.0917***
	(0.0444)	(0.0450)	(0.0210)
Loan duration	−0.3279***	0.1659***	0.0894***
	(0.0538)	(0.0384)	(0.0199)
Credit risky	0.1940	0.2216	0.1395
	(0.3343)	(0.3570)	(0.1769)
Title length	−0.0725***	−0.0753***	−0.0370***
	(0.0190)	(0.0200)	(0.0099)
Purpose (enterprise startup)	0.0622	0.1307	0.0904
	(0.3037)	(0.3365)	(0.1762)
Purpose (other purpose)	−0.5925	−0.8546*	−0.3699*
	(0.4186)	(0.4421)	(0.2087)
Purpose (short-term turnover debt)	−0.0148	−0.0300	−0.0009
	(0.2268)	(0.2469)	(0.1269)
Age	0.0184	−0.0028	−0.0026
	(0.0242)	(0.0274)	(0.0135)
Education (low)	−0.7962**	−0.8613**	−0.4423**
	(0.3450)	(0.3647)	(0.1788)
Education (not reported)	−0.4812*	−0.7473***	−0.3508***
	(0.2501)	(0.2722)	(0.1328)
Gender (male)	0.3576	0.4589	0.2714*
	(0.2685)	(0.2854)	(0.1458)
Num of children	−0.9199***	−0.8922***	−0.4358***
	(0.2797)	(0.2963)	(0.1468)
Marriage (not married)	0.0380	−0.0268	0.0014
	(0.2612)	(0.2828)	(0.1469)
Marriage (not reported)	0.9607*	0.7940	0.4145
	(0.5514)	(0.6533)	(0.3386)
Intercept		−1.8688	−1.0350
		(1.9585)	(0.9800)
N	1762	1563	1563
AIC	1315.5168	707.3733	707.0660
BIC	1400.4963	798.3974	798.0901
Log Likelihood	−641.7584	−336.6866	−336.5330

$^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

This table reports the estimation results for late loan rates. *Late* is defined as being 30 days late. Each observation is a loan. We report the point estimates, and the standard errors are in parentheses

more likely to follow peer predecessors than unseasoned investors. Such a finding seems to go against the general logic of behavioral finance, suggesting that

Table 11 Herding and default rates

	(1) Cox CPH	(2) Logit	(3) Probit
Y^s: Amount from seasoned	−0.2421	−0.3218*	−0.1895*
	(0.1850)	(0.1909)	(0.1099)
Y^u : Amount from unseasoned	0.0192	0.1470	0.0561
	(0.0848)	(0.0929)	(0.0468)
Interest rate	0.1603***	0.2041***	0.1134***
	(0.0586)	(0.0544)	(0.0310)
Loan duration	−0.6384***	0.1077**	0.0261
	(0.0619)	(0.0442)	(0.0270)
Credit risky	0.0048	0.3391	0.3100
	(0.3848)	(0.3784)	(0.1994)
Title length	−0.0494**	−0.0779***	−0.0394***
	(0.0234)	(0.0226)	(0.0128)
Purpose (enterprise startup)	0.1151	0.4825	0.4373**
	(0.3431)	(0.3588)	(0.2160)
Purpose (other purpose)	−0.1826	−0.3724	0.0650
	(0.4390)	(0.4559)	(0.2525)
Purpose (short-term turnover debt)	0.0810	−0.0260	0.2001
	(0.2779)	(0.2863)	(0.1725)
Age	0.0037	−0.0324	−0.0318*
	(0.0295)	(0.0318)	(0.0182)
Education (low)	−0.5937	−0.6608*	−0.3114
	(0.4028)	(0.3891)	(0.2091)
Education (not reported)	−0.1052	−0.7652**	−0.4076**
	(0.2989)	(0.3095)	(0.1718)
Gender (male)	−0.1935	0.1504	0.3935**
	(0.2935)	(0.2978)	(0.1977)
Num of children	−0.5105	−0.6736**	−0.2840
	(0.3247)	(0.3293)	(0.1804)
Marriage (not married)	−0.0323	0.0297	−0.0571
	(0.3071)	(0.3221)	(0.1830)
Marriage (not reported)	0.7456	1.1203	0.5836
	(0.6595)	(0.6945)	(0.3960)
Intercept		−2.0748	−1.1170
		(2.2702)	(1.2817)
N	1497	1554	1548
AIC	813.7400	595.9183	443.3659
BIC	898.7195	686.8443	534.2261
Log Likelihood	−390.8700	−280.9592	−204.6829

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

we should take a more nuanced view of herding behavior. A plausible explanation might be as follows. Although people tend to prefer a less effortful mode of processing (i.e., heuristic processing) to one that requires more time and cognitive resources (i.e., systematic processing), the heuristic and systematic information processing theory asserts that individuals are sometimes motivated to exert additional cognitive effort in order to reach a certain level of judgmental confidence, which is termed as *sufficiency principle* [6]. That is, the extent of information processing is determined by the size of the discrepancy that exists between an individual's actual level of confidence in their judgment and the sufficiency threshold (i.e., their desired confidence). Effortful information processing (i.e., systematic processing) would occur when actual confidence falls below the sufficiency threshold and should continue until this confidence gap is closed. As information manipulation is prevalent in online markets in China, investors in the debt-based crowdfunding platform may worry that some market signals, such as the lending amount from predecessors, might be fabricated by borrowers and their colluding partners [7]. Therefore, simply referring to predecessors' decisions would not produce sufficient judgmental confidence. Instead, they would exert more cognitive effort (i.e., a systematic information processing approach) and rely less on heuristic cues such as predecessors' decisions. As their investment experience grows, their investment knowledge increases [31], and they may gradually realize that their predecessors' lending amount is a credible market signal and their judgmental confidence in such herding signals, especially the seasoned predecessors' herding signals, may grow as well. As a result, compared to unseasoned investors, seasoned investors would have a greater inclination to follow heuristic cues such as peer predecessors. Such findings are consistent with Korniotis and Kumar [31]'s findings at a major U.S. discount brokerage house that experienced investors are more likely to follow "rules of thumb" and with Huang [25]'s findings of early-stage entrepreneurial investment decision making that inexperienced investors rely less on their gut feels. Such a result also echoes Caglayan et al. [4], who find that, in the crowdfunding market, experienced investors have a greater tendency to follow the herd.

Third, we discover that compared to unseasoned investors, seasoned investors have a greater tendency to follow seasoned predecessors and deviate from unseasoned predecessors. Such findings extend the traditional view that decision-makers rely much on their own judgment if they feel powerful and knowledgeable [2, 43]. The result also echoes Sunder et al. [48], who find that, in the online rating context, as rater experience grows, the positive influence of the crowd diminishes, while the influence of credible predecessors, such as friends, amplifies.

Finally, the results show that the lending amount from seasoned investors is a valid signal in predicting loan performance, while the lending amount from unseasoned investors is not. Such findings extend prior studies about the wisdom of the crowd [3, 49], implying that collective intelligence could be extracted from seasoned investors rather than from unseasoned investors in the debt-based crowdfunding market. Online debt-based crowdfunding is a delicate, complicated financial market that requires investors to be equipped with sophisticated financial knowledge. Therefore, in such markets, the local knowledge from unseasoned investors contributes little to the wisdom of the crowd.

6.2 Implications for research

This study holds several implications for research. First, we extend prior research on the signaling value of peer bids in crowdfunding by distinguishing between seasoned and unseasoned predecessors. Prior studies assume that the lending amount from predecessors is homogeneous in attracting the lending amount from a successor (e.g., [56]). The current study shows that the effects of predecessors' lending amounts are heterogeneous: investor expertise plays a significant role in judging its informativeness. Investors with greater investment expertise are more influential,therefore, lending amounts from seasoned predecessors could attract greater lending amounts from a successor. Although seasoned investors are not explicitly tagged in the crowdfunding platform, they are still distinguished by their successors and are given higher weight.

Second, we extend prior studies on information processing by distinguishing between seasoned and unseasoned investors and examine their different investment behaviors when facing the same market signals. Caglayan et al. [4] have shown that investment experience influences the pattern of investor herding. Despite the different definitions of expertise, our results are consistent with Caglayan et al. [4]'s findings, confirming that experienced investors have a greater tendency to follow the herd. We further discover that, compared to unseasoned investors, they have a greater tendency to follow seasoned predecessors and to deviate from unseasoned predecessors. Such findings imply that seasoned investors are more sensitive to herding signals and are more capable of extracting hidden information embedded in the signals. Moreover, our findings reveal that herding is less likely to occur among inexperienced investors. A plausible explanation might be that strategic herding in the crowdfunding market involves observational learning and requires sophisticated knowledge, so it is popular only among experienced investors. Such findings challenge the traditional view that inexperienced investors have greater tendencies to follow the herd.

Finally, our study shed light on how to extract collective intelligence from the wisdom of the crowd. The study shows that in a market that requires sophisticated knowledge, such as crowdfunding, decisions from unseasoned individuals are not informative; therefore, it is not wise to blindly follow the herd. Instead, investors should distinguish seasoned predecessors from unseasoned predecessors and follow seasoned predecessors' decisions. This study shows that seasoned investors are more able to extract the hidden information embedded in the herding signals, indicating that unseasoned individuals should be educated to improve strategic herding capabilities.

6.3 Implications for practice

This study provides valuable insights for crowdfunding platforms, participants, and policymakers. First, our studies show that experts play a critical role as opinion leaders in the market. Successors observe predecessors' activities and strategically follow them. Loans with greater lending amounts from seasoned predecessors are less likely to default, implying that investment performance could be improved by identifying and following seasoned predecessors. To help the crowd better extract hidden information from experts, platforms could develop tools to facilitate investors in obtaining information about predecessors. For example, a diagram depicting the distribution of predecessors' lending experience might be helpful.

Second, our findings suggest that we should be careful when extracting the wisdom of the crowd in a context that requires sophisticated knowledge, such as in the crowdfunding market. We find that little information is contained in unseasoned investors' lending amounts. Therefore, it would be dangerous if we just aggregate all investors' decisions in a naive manner. Instead, we need to differentiate between seasoned and unseasoned predecessors and give more weight to predecessors with greater expertise. As unseasoned investors are less capable of extracting hidden information, a mechanism should be designed to equip them with a better understanding of market signals.

Finally, this study sheds new light on the rational level of investors in this market, which provides valuable insights for policymaking. We discovered that seasoned investors could identify the signals from seasoned predecessors and strategically utilize them, implying that seasoned investors do behave in a rational manner. On the other hand, unseasoned investors are not capable of analyzing market signals. The bright point is that unseasoned investors might turn into seasoned investors if they have opportunities to learn and grow. We propose that the crowdfunding market should be strictly regulated at the early stages due to the existence of amateur investors, but the more important thing for policymakers is to give the market some patience and time. We believe that as time goes by, the market will eventually grow mature.

6.4 Limitations and further studies

Although this study makes significant contributions to the literature and has important managerial implications, it also has several limitations. First, our study is based on the transaction data of only one crowdfunding platform in China. As there are quite a few crowdfunding platforms all over the world, which may use slightly different lending mechanisms, whether the findings in this platform can be applied to other lending platforms is unknown. Future studies could use data from other lending platforms to cross-validate the findings in this study.

Second, although we controlled for as many variables as we could in our regression models, other important confounding factors may still exist. They are absent from our study not by design but due to the unavailability of relevant data. For instance, some characteristics of borrowers, such as borrower social capital and listing appearances, may have significant influences on lending outcomes [16, 20] but are not included in our regression model due to the lack of such data. Therefore, our results may suffer from omitted variable bias (OVB). Future research could incorporate more variables into the research model to examine the validity of our findings.

Finally, the behaviors of borrowers and investors may change with time as crowdfunding platforms are still evolving. The advancement of information technology and the development of the social economy may also bring about significant changes in participants' behaviors. To have a good understanding of the evolution of the market, longitudinal studies could be conducted in future research.

7 Conclusions

Our study provides a preliminary examination of the role that experts play in the debt-based crowdfunding market, a form of peer economy that is characterized as democratizing the access to tasks available only to professionals. Using datasets from a leading online debt-based crowdfunding platform in China, we find that (1) seasoned predecessors are more influential in attracting lending amounts from successors, (2) seasoned investors are more sensitive to herding signals in the market, and (3) the lending amount from seasoned investors is more informative than the lending amount from unseasoned investors in predicting loan repayment performance.

For academia, our work highlights the need to better understand the role that experts and crowds play in the peer economy context. Although the peer economy grants crowds opportunities to conduct complicated financial activities, such as investing, our study suggests that experts should still play a critical role as opinion leaders in such a market. For practitioners, our work suggests that the wisdom of the crowd should be extracted from experts rather than from crowds. For policymakers, our work suggests that some patience and time should be given to the crowdfunding market, waiting for it to grow mature.

Appendix A: Results of investor participation decision

	(1) Participate
Seasoned (1 = yes)	− 0.0088*** (0.0024)
Amount requested	0.2713*** (0.0025)
Interest rate	0.0110*** (0.0003)
Loan duration	− 0.0291*** (0.0004)
Credit risky	− 0.2841*** (0.0030)
Title length	− 0.0003 (0.0002)

	(1) Participate
Purpose (enterprise startup)	0.0538*** (0.0042)
Purpose (other purpose)	0.1000*** (0.0040)
Purpose (short-term turnover debt)	0.0387*** (0.0028)
Purpose (not reported)	0.4559*** (0.0071)
Borrower age	0.0008*** (0.0002)
Education (low)	−0.0902*** (0.0034)
Education (not reported)	−0.2517*** (0.0029)
Gender (male)	−0.0804*** (0.0034)
Num of child	−0.0059** (0.0030)
Marriage (not married)	−0.0156*** (0.0036)
Marriage (not reported)	−0.1131*** (0.0079)
Intercept	−4.1472*** (0.0239)
N	6,520,938
AIC	1,191,191.3033
BIC	1,191,437.7328
Log Likelihood	−595,577.6516

Appendix B: Loan level characteristics

		Mean	SD	Min	Max
Y^s: Amount from seasoned	Lending amount from seasoned investors	4940.770	5353.760	100.000	77,727
Y^u: Amount from unseasoned	Lending amount from unseasoned investors	1786.219	1773.565	0.000	20,072
Amount requested	Request amount of a loan (RMB)	6473.993	6156.625	3000.000	88,000
Interest rate	Interest rate provided by a borrower (%)	16.144	4.127	5.000	22
Loan duration	The number of months the borrower makes payments	5.561	3.477	1.000	12

		Mean	SD	Min	Max
Credit risky	1 if a loan's credit rating is E or HR, 1 otherwise	0.153	0.360	0.000	1
Title length	Number of characteristics in the title of a loan	18.519	5.846	10.000	30
Late	Whether a loan is late for more than 30 days	0.062	0.242	0.000	1
Default	Whether a loan is late for more than 90 days	0.048	0.213	0.000	1
Purpose (base)	The purpose of a loan is for goods consumption	0.305	0.461	0.000	1
Purpose (enterprise startup)	The purpose of a loan is for enterprise startup	0.111	0.314	0.000	1
Purpose (other purpose)	The purpose of a loan is for other purpose	0.177	0.382	0.000	1
Purpose (short-term turnover debt)	The purpose of a loan is for short-term turnover debt	0.407	0.491	0.000	1
Age	The age of the borrower	30.537	5.337	20.000	54
Num of child	Number of children that the borrower has	1.492	0.589	1.000	4
Education (base)	The borrower has a college diploma or higher	0.468	0.499	0.000	1
Education (low)	The borrower has a high school diploma or lower	0.142	0.350	0.000	1
Education (not reported)	The borrower education level is not reported	0.389	0.488	0.000	1
Gender (base)	The borrower is a female	0.172	0.377	0.000	1
Gender (male)	The borrower is a male	0.828	0.377	0.000	1
Marriage (base)	The borrower has married	0.578	0.494	0.000	1
Marriage (single)	The borrower has not married	0.401	0.49	0.000	1
Marriage (not reported)	The borrower marriage status is not reported	0.021	0.143	0.000	1

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