Search Frictions in Crowdfunding Markets*

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Abstract

This paper studies, theoretically and empirically, how search frictions affect price competition and funding allocation in the crowdfunding market. I develop a dynamic many-to-one matching model with fixed sample search, à la Burdett and Judd (1983), and show that borrowers employ mixed strategies in setting interest rates in a unique stationary equilibrium. I construct a novel dataset on a large panel of fundraisers' behaviors and find evidence of persistent rate dispersion and funding mismatches, which are consistent with the theoretical predictions of the impact of search frictions. More importantly, the model implies that in a many-to-one matching market, interest rate dispersion caused by search frictions facilitates investor coordination and hence improves matching efficiency relative to a no friction environment. According to a non-parametric estimation, I find that with dispersed rates, the coordination effect can improve the aggregate funding probability by 28% compared with a random matching context.

Key Words: Search Friction, Many-to-one matching, Crowdfunding, Coordination.

JEL Classification: C78, D43, D83, L86

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1 Introduction

Since seminal work by Stigler (1961), search frictions have been used to explain many economic phenomena. The friction prevents consumers from learning prices perfectly, and thereby softens sellers' competition. While search frictions may be smaller in online markets than tranditional retail sector, growing evidence shows that they are still significant (e.g., Hong and Shum (2006), De los Santos et al. (2012)). For instance, it is observed that persistent price dispersion exists among otherwise homogeneous products. This paper attempts to study search frictions in online crowdfunding markets, where they are particularly important as each borrower has to be matched with many investors.

Online crowdfunding is an emerging sector that allows borrowers to receive external finance from individual investors without traditional banking intermediaries. Borrowers in such markets specify financial goals that must be met by attracting sufficient funds in a certain processing period. If this goal is not met, the funding procedure fails and all involved investors have to search again and reinvest. Thus, the crowd of investors must coordinate on which borrowers to fund. In this paper, I show that in equilibrium without search frictions, borrowers engage in Bertrand competition and investors randomly select the project in which to invest. However, with search frictions, borrowers' mixed strategies induce rate dispersion, which serves as a coordination mechanism for the investors. I show that this coordination raises the proportion of successful matches and thereby raises welfare.

The specific motivation for this paper is the evidence observed from online crowdfunding loan markets. By documenting novel data including information on 300,000 listings from Hongling Capital, the largest crowdfunding loan market in China, I find that even if the listed loans are of identical quality in terms of duration and risk, (1) rate dispersion is always present in the market. In addition, by observing each listing's funding process, I find that (2) a large number of high-rate projects were not funded, while some low-rate loans posted during the same period and exhibiting the same quality were successfully financed. These facts seem to suggest that frictions such as investors' search patterns play a significant role in the market, despite the availability of competing fundraisers. Moreover, by tracking listings' funding dynamics, I find that (3) for most of the listings, funding speed, as measured by time between two successive bids, is independent of funding progress. The third finding is puzzling because the platform discloses each listing's funding progress, which intuitively should act as an exogenous coordination mechanism that enhances a listing's likelihood of being funded. This finding is also inconsistent with the herding effect discussed by Zhang and Liu (2012) and Kuppuswamy and Bayus (2014). To resolve this puzzle, by taking high-frequency screenshots of the website, I observe that the market has a relatively high trading speed and it is time-consuming for investors to process and update a large amount of investments. Therefore, the dynamic information disclosure regarding listings' funding status always has a delay or even a malfunction, thereby preventing investors from learning others' behavior from this information. The empirical patterns observed refer to the main finding of the paper, namely that many-to-one matching markets are subject to a coordination problem, which rate dispersion helps to address.

In an effort to explain the empirical evidence observed in the data using search frictions, I construct a dynamic many-to-one matching model embedded with fixed-sample search technology à la Burdett and Judd (1983). Consistent with the actual market structure, the model consists of borrowers and investors who enter the market over time. Each borrower's project requires N units of fund. Upon entry, borrowers post their loan requests and commit to interest rates. On the other side, investors visit the market and make investment decisions based on their observations. Each investor is endowed with just one unit of fund. Once a loan request is matched with a sufficient number of investors, borrowers and matched investors will leave the market with their respective revenues. As borrowers are waiting for investors, they may be thrown out of the market at a constant rate.[1] Regarding the search technology, investors enter the market, randomly sample a finite number of listings, and select one in which to invest. From the borrowers' perspective, they meet investors with a Poisson process whose intensity is endogenously determined by the market depth. Conditional on a meeting, the matching probability depends on the listing's ranking in the investor's sample.

The model highlights several features and imperfections in crowdfunding markets. First, investors can only sample a limited number of listings. As observed in the data, this feature

[1] In most online crowdfunding markets, a fixed deadline is required. Because this is not our main focus, I simplify the model by incorporating the Poisson death shock, which allows me to derive comparative statics in a stationary environment.

generates the possibility that all listings fail to secure funding perfectly. Moreover, this feature incentivizes borrowers to charge lower interest rates. Second, to study the mixed effect of frictional search and noisy information disclosure, I assume that investors make independent decisions without observing the listings' investment history, in line with the fact that the progress disclosure mechanism malfunctions and there is no exogenous coordination mechanism. Instead, investors form beliefs of observed listings' funding status by observing interest rates.

The model produces two main results. First, I show that a stationary equilibrium exists and is unique. In that equilibrium, borrowers employ mixed strategies in setting interest rates. The result explains how search frictions induce rate dispersion in the market even if loans are of the same quality.

Second, in terms of matching efficiency, I show that in a one-to-one matching environment, rate dispersion simply determines how the surplus is divided between the two sides of the market and has no effect on social welfare. However, in the many-to-one matching environment, when investors make their decisions independently, the rate dispersion caused by search frictions endogenously creates ex post heterogeneity among the listings, which will act as a mechanism that facilitates investor efforts to sort observed listings. Comparatively, absent frictional search, borrowers will engage in Bertrand competition such that the sorting mechanism disappears, as interest rates are identical. Therefore, the proportion of successful matches in the Bertrand competition scenario will be the same as that in a random matching environment. In this sense, a certain level of search friction is beneficial to the allocation efficiency of the market. The main insight of the result can be illustrated by a simple example. Consider two borrowers, each of whom requires two dollars of funding, while there are two independent investors, each of whom has only one dollar. Borrowers compete by committing to an interest rate. Since there are two dollars in total on supply side, the first best situation is to allocate them to any one of the two projects. When both investors can observe the two rates perfectly, however, borrowers will set interest rates at the perfectly competitive level. Then, facing identical rates, absent coordination, each of the two investors will randomly choose which borrower to support. In this case, the probability of a successful funding is 1/2. However, if each investor has some frictions in price investigation such that one can observe both rates with probability $\lambda \in (0,1)$, borrowers obtain some market power and employ mixed strategies in setting rates. In this case, provided that both investors observe two rates, they can perfectly coordinate to invest in the project with a higher rate. Therefore, the probability of having is $\frac{1}{2}(1+\lambda^2)$, which is larger than that in the Bertrand competition scenario and hence improves allocation efficiency.

To quantitatively measure the welfare impact due to search frictions compared with the no-friction environment, I develop a non-parametric method to estimate the search friction primitive, which is defined as the distribution of investors' sample size in the model. I show that the distribution can be uniquely identified and measured by the loans' funding probabilities with respect to their percentile rank in the market. Accordingly, I transfer the model from absolute terms interest rate level to relative terms as percentile. The benefit of the transformation is that I need not to identify and estimate the parameters regarding the value of interest rates. The simplification allows me to utilize more observations to estimate funding probability, which increases efficiency. According to the estimation, the welfare gain is approximately 28% compared with that when rate dispersion is eliminated.

Section 5 extends the model such that loan size is another choice variable in borrowers' loan contract that aims to study rate distributions across different sizes of loans. Consistent with the analysis of the data, given search frictions, larger loans have higher interest rates, which implies that borrowers consider the "crowd" effect and therefore provide a risk premium to investors for the possibility of investment failure. Specifically, I show that under search frictions, borrowers who issue small loans and those who issue large loans randomize interest rates within two disjoint intervals. Moreover, investors are indifferent between the lower bound of larger loans' rate distribution and the upper bound of smaller loans' rate distribution. The result implies that the risk premium is high enough that investors strictly prefer a larger loan.

Related Literature

The paper is related to several strands of literature. First, the theoretical framework dates back to seminal papers on static search models, such as Stigler (1961), Varian (1980), and Burdett and Judd (1983). My model shares the common setup that price investigation is costly or frictional for buyers, which gives sellers some market power to charge higher prices. In the equilibria of such frameworks, sellers will employ mixed strategies, thereby generating price dispersion, even if goods are homogeneous. Dynamic versions of Burdett and Judd (1983) include works such as the Burdett and Mortensen (1998) on-job-search model and Head et al. (2012) monetary search model. The difference between dynamic and static models is that there are frequent entry and exit events.[2] While most of the classical models discuss single product search, there is a strand of research discussing multiproduct search. Namely, consumers look for complementary products from different sellers (e.g., McAfee (1995) and Zhou (2014)). However, since the trading volume is not affected, the main impact of search is how the surplus is split between the two sides of the market. My work alters the frameworks assuming that a seller needs many buyers.[3] Then, search friction has a positive effect on facilitating coordination and hence improves welfare.

Second, the paper is related to recent empirical studies on price dispersion in online markets following the rapid development of e-commerce. For example, Brynjolfsson and Smith (2000), Clay et al. (2001), and Goolsbee (2001) attempt to understand the nature of search costs by comparing the degree of price dispersion between online and traditional retail markets. Further, Hong and Shum (2006) estimates a Burdett and Judd (1983) non-sequential search model using price data for online book retailers. Other studies include De los Santos et al. (2012), who uses consumers' web search histories to study their search behavior and concludes that a non-sequential search model better describes buyers' behavior in online markets. A similar methodology is applied by Hortaçsu and Syverson (2004), who studies the rate dispersion in S&P500 funds. All the markets that make the focus of the above works feature long-lived sellers and bilateral trading, while my work focuses on a market with frequent inflows and outflows with many-to-one transactions.

Finally, the paper contributes to the growing literature on crowdfunding markets. As mentioned above, Kuppuswamy and Bayus (2014) and Zhang and Liu (2012) attempt to empirically understand investor dynamics over project funding cycles. They conclude that contributions by peer investors will exacerbate network externalities and hence affect others'

[2] A comprehensive summary and review of the research can be found in Baye et al. (2006).

[3] If we treat borrowers as loan sellers and investors as loan buyers

decisions. My work studies the problem of investors having no information on their peer investors' decisions. Moreover, my work not only considers the dynamics of a project's funding process but also the competition among fundraisers. Other papers on crowdfunding include Wei and Lin (2013), who studies auctions in crowdfunding markets [4], Kawai et al. (2014), who identifies and estimates a signaling model using data from a US crowdfunding credit platform, and Strausz (2016), who studies demand uncertainty and moral hazard problem in crowdfunding market from a mechanism design perspective. All of these works assume that a fundraiser is a monopolist on the borrower side. Some census data regarding the crowdfunding market are surveyed in Agrawal et al. (2013).

The remainder of this paper is organized as follows. Section 2 introduces the data and summarizes important empirical evidence. Section 3 introduces the model and characterizes the equilibrium. Section 4 discusses the welfare implications of the theory and estimates model primitives. Section 5 discusses an extension of the model with endogenous size. Section 6 concludes the paper. Additional empirical tests, technical proofs, tables, and figures are attached in the appendixes.

2 Institutional Background and Data

I collected data from Hongling Capital, Inc. (or my089.com), one of China's largest online crowdfunding loan platforms, based in Shenzhen. In this section, I describe how the platform operates. To demonstrate that rate dispersion exists among nearly homogeneous loans, I devote particular emphasis to two types of listings, called "primary" and "secondary" loans. Then, I report summary statistics and empirical evidence.

The trading mechanism in the platform works as follows. (1) Borrowers enter the platform, post information such as the amount requested, purposes and a brief personal introduction, and commit to interest rates and the duration of the loan. (2) Investors view the listings and choose which to invest in. (3) If the requested amount is raised before the deadline[5], borrowers receive the money and repay the debt according to committed terms. (4)

[4] All principal platforms have since abandoned this mechanism.

[5] At my089.com, the deadline is 2 days, but most of the projects are delisted before then.

Otherwise, the loan will be canceled, and the money will immediately be returned to the investors.

2.1 Data Description

2.1.1 Data Overview

The dataset has a horizon of 4 months (Jan 1st - May 1st, 2015) and includes information on 508,888 listings, of which 216,402 are fully funded. The average interest rate is approximately 14.03%, and the average maturity is approximately 130.747 days (weighted by loan size). The average daily trading volume is 155 million Chinese Yuan(CNY) (approximately 25 million US Dollar(USD)). The data consist of three parts

- **Loan Information** records basic information regarding each listing, such as the borrower's ID, loan size, interest rate, and duration.
- **Bidding Record** has information on a listing's bidding history, which records the time and amount invested for each participating investor. One issue to note is that the information only includes loans that were fully funded.
- **Snapshot** records all listings' funding dynamics on the platform every 10 minutes. It allows us to continuously track the platform's characteristics, such as the pace of funding and new postings.

2.1.2 Loan Classification and Dealership

The loans are classified into several categories, but 99.57% of trading volume is generated by two types. I name them "primary" and "secondary" loans due to their features. A detailed description is provided in Table 1.

Primary Loans The first type is called "primary" loans because they are listed by the platform itself. Moreover, the platform also monitors these projects and guarantees investors' returns. In this sense, the platform is not only an informational intermediary but also works like a bank, which finances and monitors the borrowing side while absorbing deposits and providing insurance to the other side.[6].

The primary loans account for approximately 31% of total trading volume. They have large sizes, high returns and long maturities. In my sample, all primary loans have an annualized interest rate of 18%. The average size is 3.8 million CNY, and the average duration is approximately 611 days. Moreover, all primary loans were fully funded in my sample.

Secondary Loan In addition to primary loans, the platform allows its clients to issue short-term loans using their assets (either cash deposited or unexpired investments) within the platform as collateral. The most commonly used collateral is unexpired primary loans. To some extent, the short-term loan is a financial derivative with primary loans as an underlying asset, and I thus term such loans "secondary". As mentioned above, primary loans are return guaranteed, and hence, secondary loans are also secured. If a secondary loan's payment is delayed, the platform will freeze the debt holder's asset and prepay the investors.

Compared with primary loans, the average maturity and rate of secondary loans are smaller. On average, the maturity is 27.98 days, while the interest rate is 12.81%. Such loans represent approximately 68% percent of the market. In the sample, secondary loans' funding probability is approximately 40%.

In terms of market risk, because primary loans are return guaranteed and secondary loans backed by within-platform collateral, all of the listings in the market share the same systematic risk.

Dealership through Secondary Loans As illustrated in Table 1, there is an approximately 5% difference between the returns on primary and secondary loans. This creates an opportunity for the platform's clients to make a profit from investing in long-run primary loans by issuing short-term secondary loans. Figure 1 illustrates the daily transaction volumes of primary loans and one-month net value loans, which are highly correlated. In

[6]Due to the lack of a national credit system, most of China's P2P lending platforms guarantee investors' returns by monitoring the projects issued by the platforms. If default occurs, a platform uses its reserve fund to repay investors. Wang et al. provides a detailed introduction to China's online lending market.

addition, as the user ID of each borrower and bidder on a listing can be observed, the data allow us to track every registered customer's lending and borrowing behavior simultaneously. There were 7,746 of a total of 109,828 users who engaged in both borrowing and lending. Using this information, I identified dealer behaviors within the market. As illustrated in Figure 2 below, overall 63.04% of the primary loans are contributed to by "dealers" using money borrowed through secondary loans.

2.2 Empirical Facts

The dealers' behavior creates an ideal natural laboratory to study competition in crowd-funding markets, as it unifies the risk and value of each borrower's project, which helps us to rule out other unobservable heterogeneity that may also cause price dispersion. In this section, I report key empirical evidence that motivates the main questions of the paper. I focus only on empirical patterns regarding 1-month secondary loans made for the purpose of investing in primary loans. The selection procedure generally ensures that the listings in our sample are of the same quality in terms of their

(a) Duration: 1 month

(b) Value: primary loans' return

(c) Risk: platform's systematic risk

Accordingly, our restricted sample has a total of 297,685 listings, of which 126,121 were fully funded. The average size and rate are 31,090 CNY and 14.32%, respectively. On average, the number of investors per listing is 6.36, conditional on the listing being fully funded. The summarized statistics are reported in Table 2.

Funding Probability

Our first evidence for the existence of market friction is the funding probability of the listings in the market.

Fact 1. *While funding probability is increasing in the interest rate, there is a significant failure rate for listings of all rate ranges.*

According to Table 3, funding probability is increasing in the interest rate. However, even for listings with the highest interest rate level ($\geq$16%), the funding probability is only approximately 60%, while listings with a lower rate still have an approximately 20% chance of being funded. Further, to avoid time-dependent variation such as market demand and supply, I compute the funding probability by percentile during each hour and observe a similar pattern. According to Table 4, for listings at the 80th percentile, the funding probability is only approximately 65%, while listings at the 20th percentile have a success rate of approximately 30%.

Interest Rate Variation

The second set of evidence concerns interest rate dispersion. As shown in Table 3, the interest rates for 1-month loans range from 10% to 17%. As predicted in many theoretical works (e.g., Burdett and Judd (1983)), when search frictions play a role, every seller employs identical mixed strategies such that the market will have a non-degenerate price distribution. Alternatively, price dispersion can simply be described by unobservable individual-level heterogeneity. For instance, it is possible that fundraisers with high-quality projects might be willing to offer higher interest rates. Although I have argued that the borrowers have nearly identical returns (primary loans) on their projects in our data, to demonstrate that search friction is the main cause of rate dispersion, it is necessary to compare individual-level rate dispersion and market-level rate dispersion. Suppose at individual level, the dispersion level is significantly smaller, then it might be the case that rate differentiation is induced by some unobservable heterogeneity in stead of mixed strategy induced by search friction. However, in most empirical works (e.g., Hong and Shum (2006), De los Santos et al. (2012)), the price distribution is generated from a static snapshot of the market. Hence, those works generally assume that price dispersion results from the use of mixed strategies. Fortunately, in my data, I am able to observe repeated listing behavior by the same borrower, which allows me to compare rate distributions at the individual and aggregate levels.

To measure rate dispersion, I employ two measures for robustness. First, following

Jankowitsch et al. (2011), I define dispersion as follows

$$d_t = \sqrt{\frac{1}{\sum_{k=1}^{K_t} w_{kt}} \sum_{k}^{K_t} (r_{kt} - \bar{r}_t)^2 \cdot w_{kt}}$$

In the formula, r_{kt} is the interest rate for listing k in period t. $\bar{r}_t$ is the weighted average rate in period t. Further, w_{kt} represents the weight imposed on listing kt. If we weight each listing equally, then $w_{kt} = 1$. Alternatively, we can weight each listing by its size. In brief, this measure represents the root mean squared difference between the traded rates and the respective valuation based on a weighted calculation of the difference. In our sample, on average, each borrower posts 4.29 listings per day. I compare dispersion at the individual level with aggregate dispersion on daily and weekly bases. For comparison, I also compute the daily and weekly dispersion for all listings in our sample.

According to Table 5, the daily and overall levels of dispersion are slightly smaller than that at the aggregate level, while dispersion at the weekly level is slightly larger. This suggests that individual-level dispersion plays a prominent role in market-level dispersion. Second, I perform a simple comparison of the minimum and maximum rates quoted by different borrowers. As indicated in Table 6, there is no significant difference between dispersion at the aggregate and individual levels. [7] In summary,

Fact 2. *Individual-level interest rate dispersion is similar to that at the aggregate level.*

Progress Effect

The third motivation for the paper is the puzzle that investors do not respond to listings' funding progress even if the information is disclosed by the platform. Intuitively, a listing with more advanced progress will be filled faster than those that have just been listed. According to Zhang and Liu (2012) and Kuppuswamy and Bayus (2014), herding behavior plays an significant role in listings' funding dynamics. I implement a similar empirical strategy to theirs but observe that this effect is weak. Specifically, to determine whether

[7] For the min/max measure, as an individual's number of listings is much smaller than the total level, I consider the min/max for individuals but 10th percentile/90th percentile for the aggregate-level data. Hence, in principle, aggregate-level statistics should be somewhat smaller.

funding is accelerated by funding progress, I regress the time interval between two successive bids on the listing's lagged progress, controlling for other variables[8].

$$DT_{it} = \alpha PROGRESS\ CUMULATED_{it-1} + X_{it}\beta_1 + X_i\beta_2 + X_t\beta_3 + \varepsilon_{it}$$

The model (Panel 1 in Table 8) predicts that when the progress is increased by 10%, the funding speed can be increased by approximately 37 seconds. The impact is very small compared with average funding duration, which is approximately 65 minutes in the sample. Then, I separate the sample into two groups. In the first group, the funding duration is less than 90 minutes. It contains 90% of the listings in the sample, while listings in the second group have longer funding times. According to panel 2, the majority of the listings' funding processes are independent of the amount of funding secured to date. However, even for listings that required more time to be funded, the increase in the funding rate attributable to funding progress is quite limited (10% progress difference equates to an approximately 6-minute decrease in funding time). The results of the reduced-form analysis suggest that funding progress plays an insignificant role in listings' funding dynamics, especially for the trading environment with relatively high frequency.

Quality of Progress Bar Another finding indicating that progress may not be a useful tool to coordinate investors is that there is a significant malfunction in the progress bar shown on the website. I take snapshots of the website every ten minutes, which includes the progress of each listing. Moreover, I collect the investment records of all the successful loans that contain investors' investing time and amount. We found that the website has certain level of delay or malfunction in reporting listings' funding progress across all listings. Figure 4 shows the delay measured by percentage. The investigation consists of 124,191 listings, of which 75,860 has a progress delay at different levels. Moreover, 33,257 listings' progress bars always stopped at 0% during the funding process.

In summary, the imperfect funding probability together with persistent rate dispersion

[8] In their analysis, because both successful and failed listings' funding dynamics are observable, they measure the correlation between lagged progress and the probability of generating one more investor. However, in my data, because the platform erases bidding records for failed loans, I can only track funding dynamics for successful listings. Therefore, I use funding speed as the proxy to text herding behavior

at both the aggregate and individual levels provide clear evidence of market friction and imperfect competition among borrowers. Moreover, the errors in the information regarding funding progress prevents investors from effectively coordinating among themselves. Motivated by these facts, I introduce the structural model in the next section.

3 Model

In this section, we introduce a dynamic search model with a many-to-one matching environment, assuming that each borrower requires many units of funding but each investor has only one unit to provide. In essence, borrowers enter, post an interest rate and wait to be funded. Investors visit the market, sample a finite number of listings and choose the most preferred one in which to invest. After a borrower and enough investors are matched, investors receive a committed return while the borrower retains the profit, and both parties leave the market.

3.1 Model Ingredients

Time is continuous, and the market consists of two sides - borrowers (who are referred to using the feminine pronoun below) and investors (who are referred to using the masculine pronoun below).

Borrowers At each instant, a measure $L \cdot dt$ of new borrowers enters the market. Each borrower requires N units of external financing, and the projects are of the same value $N \cdot v$. Upon entry, borrowers post an interest rate r and then wait to be funded. During the funding process, a borrower may exit the market due to a Poisson death shock with intensity $\delta > 0$. Conditional on being funded, a borrower pays each investor r and leaves the market with profit $N \cdot (v - r)$.

Investors The instantaneous investor inflow is $I \cdot dt$. Each investor has one unit of money to invest. Assume that investors have the same reservation rate $r_0 < v$. In terms of investors' payoff, in the one-to-one market, an investor's utility from investment is simply r, while in the many-to-one environment, due to the risk of failure, his payoff could be represented as expected utility, which will be described shortly. For simplicity, we assume that investors are short-lived and invest only once. If the listing invested in encounters a death shock, all matched investors will leave the market with r_0 permanently.[9].

Search and Matching Upon entry, an investor randomly observes $\ell \in \mathbb{N}_+$ listed projects but can invest in a maximum of one. For each listing in an investor's sample, I assume that

Assumption 1. *Investors can observe the rate r and size N of the ℓ listings in the sample.*

To guarantee that there are always listed projects, whose stock is denoted $\mathcal{L}$, I assume that

Assumption 2. $N \cdot L > I$.[10]

I have yet to impose any structure on the distribution of ℓ. I will discuss how different search technologies affect market equilibrium in the characterization section below. On the other side of the market, after being posted, a listing waits passively for investments. Assume that each listed project can meet an investor with a Poisson intensity η, which will be endogenously determined by

$$\mathbb{E}(\ell) \cdot I = \eta \cdot \mathcal{L}$$

In the expression, the LHS is the total number of views by investors at each instant, while the RHS describes the same number but from the borrowers' perspective. In principle, the larger the investor inflow I, the higher the expected value of ℓ, and a lower the number of listed projects $\mathcal{L}$ will result in more views of a given project. In terms of matching, assume that conditional on being met, a listing with rate r has a probability $p(r)$ of being matched.[11] Therefore, $\eta p(r)$ is the effective matching intensity. In brief, a borrower meets investors sequentially and can be fully funded only if matched with N of them.

[9] Alternatively, the model can easily be extended by assuming that an investor can re-sample by paying a cost $c > 0$. If so, the only difference is that the reservation rate r_0 will be endogenously determined. Specifically, when $c = 0$, this is equivalent to investors having perfect information on the market's rate distribution

[10] If $I > N \cdot L$, then at each instant the market will be cleared immediately. We rule out the uninteresting case and only focus on $N \cdot L > I$.

[11] I will determine the function $p(r)$ in equilibrium.

3.2 Strategy and Equilibrium

In this section, I formulate agents' problems and describe aggregate variables. Then, I define the equilibrium.

Agents' Problem

To characterize the borrower's problem, denote $P(r)$ as the probability of being funded if the interest rate is r. Thus, borrower's problem is to choose an interest rate to maximize expected profits

$$\hat{\pi} = \max_{r} P(r) \cdot N(v - r) \tag{1}$$

Here, I do not impose any assumption on the borrower's strategy, which could either be pure strategy or mixed strategies. In general, denote the strategy as a rate distribution $F(r)$.

An investor's problem, however, is to choose the project with largest expected utility in his sample. Because a project's progress is invisible to investors and N is the same across all listings, the observed interest rates are the only information available to investors. Therefore, one needs to form beliefs on the funding probability of a listing with rate r conditional on his own contribution, denoted $\tilde{Q}(r)$. Thus, an investor's expected payoff can be represented as

$$u(r) = \tilde{Q}(r)r + (1 - \tilde{Q}(r))r_0$$

Furthermore, denote $Q(r)$ as the actual funding probability. In equilibrium, the belief has to be consistent for all r, i.e.,

$$Q(r) = \tilde{Q}(r) \tag{2}$$

In terms of the equilibrium concept, because both sides of the market are homogeneous, I search for a symmetric equilibrium. That is, borrowers implement the same strategy to set interest rates, while investors follow the same rule to invest.

Aggregate Variables

In addition to symmetry, I focus on the stationary environment in which the market's aggregate variables and distributions are invariant over time. First, in equilibrium, the number of meetings has to be balanced. As mentioned above, we have

$$\eta \cdot \mathcal{L} = \mathbb{E}(\ell) \cdot I \tag{3}$$

Next, the distribution of listings should be invariant with respect to time. In the model, each listing has two attributes - rate r and progress $n \in \{0, 1, 2 ... N-1\}$. Denote the density as $g(r, n)$, then in equilibrium

$$\begin{aligned} \mathcal{L}g(r, n-1)\eta p(r) &= \mathcal{L}g(r, n)(\eta p(r) + \delta) \\ Lf(r) &= \mathcal{L}g(r, 0)(\eta p(r) + \delta) \end{aligned} \tag{4}$$

The LHS of the first equation is the measure of projects that are advanced from $n-1$ to n, while the RHS is the outflow of projects with (r, n) due to making one unit of progress and death. The second equation describes the same balance but for new listings. Note that $f(r)$ is not only the borrowers' strategy but also the probability distribution of new entrants. In addition, define $g(r) \equiv \sum_{n=0}^{N-1} g(r, n)$ as the density of listings with rate r and $G(r)$ defined as the CDF of $g(r)$. The last condition required for stationary equilibrium is that the number of matches should be balanced. Because in equilibrium, $r \geq r_0$ for all listings, each investor invests in exactly one in his sample. However, for each listing with rate r, its matching intensity is $\eta p(r)$; therefore,

$$I = \mathcal{L} \int_r g(r) \eta p(r) dr \tag{5}$$

Thus far, I have demonstrated all conditions required for a stationary equilibrium. In summary,

Definition 1 (SE)**.** Given state variables $\{L, I, N\}$, parameters $\{\delta, r_0, v\}$, and search technology $\{\Pr(\ell), \ell \in \mathbb{N}_+\}$, a **stationary equilibrium** consists of

(i) Borrower's pricing strategy $F(r)$.

(ii) Investor's decision rule and belief $\tilde{Q}$;

(iii) Intensity of meeting η;

(iv) Total measure of listings $\mathcal{L}$; and

(v) Rate distribution $G(r)$,

such that

- Borrower's profit is maximized — Equation (1);
- Investors' decision rule is belief-consistent — Equation (2);
- Balance of meetings — Equation (3);
- Rate distribution is invariant of time — Equation (4);
- Balance of matches — Equation (5).

3.3 Existence and Uniqueness

Because investors' decisions are made based on their belief $\tilde{Q}(r)$, an equilibrium might not be unique. For the present, suppose that all investors are endowed with the belief that $\tilde{Q}(r) > 0$ if and only if $r = r^*$ for some arbitrary $r^* > r_0$; then, there might exist equilibria in which all borrowers will choose r^* while investors invest up to r^*. In the remaining analysis of the paper, I exclude such unrealistic equilibria and restrict attention to monotonic decision rule. Namely, when listings' funding progress is invisible to investors and N is the same across all listings, an investor will choose the largest r in his sample. I will show below that the decision rule it is belief-consistent.

Because the aim of the paper is to study the impacts of search frictions, the properties of ℓ's distribution play a significant role in determining the equilibrium. For instance, there are two special cases.

Proposition 1. *When* $\Pr(\ell > 1) = 1$, $r = v$ *(Bertrand Competition). When* $\Pr(\ell = 1) = 1$, $r = r_0$ *(Monopoly).*

According to the proposition, if investors can always sample more than one listing and compare them, then borrowers are engaging in Bertrand competition. However, if each investor can see only one listing in his sample, then borrowers have all of the market power, and the interest rate will degenerate to $r = r_0$, which is the famous result shown in Diamond (1971). In the rest of the paper, we will maintain the following assumption:

Assumption 3. $\Pr(\ell = 1) \in (0, 1)$.

There are several possible interpretations of Assumption 3. At the individual level, randomness may emerge because the number of listings in the market is stochastic; although in a stationary environment, it is constant on average. Therefore, some investors can observe more while others can only observe one. From the perspective of the whole population, it might be the case that some investors treat searching and sorting as a costly behavior and tend to invest in the first project they meet in the market. Thus, the borrowers are facing a probability distribution of different types of investors. Therefore, I do not impose any specific structure on the distribution of ℓ, except for Assumption 3.[12] Given Assumption 3, following Burdett and Judd (1983) and Varian (1980), it is easy to show that in any symmetric equilibrium, borrowers never choose pure strategy or any point of masses.

Lemma 1. *Under Assumption 3, there is no symmetric equilibrium in which all borrowers set the same rate or choose some rate with strictly positive probability.*

Proof. The logic of the proof of Lemma 1 is simple. Suppose that borrowers implement pure strategy $r < v$; then, a small upward deviation will significantly increase the probability of success while the loss in payoff is small. If $r = v$, then according to Assumption 3, deviating to r_0 will generate strictly positive profits. $\square$

Based on Lemma 1, we focus on characterizing a mixed strategy equilibrium with a continuous distribution function $\{F(r), f(r)\}$ with support $\mathbf{r} = [\underline{r}, \bar{r}]$. Then, we have an immediate result as follows.

Lemma 2. *In equilibrium,* $\underline{r} = r_0$.

[12] In the literature, there are many alternatives to define the distribution of ℓ. For example, in Burdett and Menzio (2013), ℓ takes value 1 (captive) or 2 (non-captive). Alternatively, Hong and Shum (2006) assume that investors are heterogeneous in unit search costs. The lower the cost, the larger the sample one could draw. In equilibrium, the unit cost is equal to the marginal benefit from drawing one more sample.

In words, the lower bound of price dispersion is always the investors' reservation rate in equilibrium. The logic behind Lemma 2 is that, if $\underline{r} > r_0$, for all investors, deviating to r_0 will maintain the same probability of success because the only way in which the listing is funded is if the counterpart investor has $\ell = 1$. However, reducing the interest rate to r_0 will increase the return conditional on being funded. Hence, choosing r_0 is a profitable deviation. In equilibrium, by the indifference principle of mixed strategies, all rates $r \in \mathbf{r}$ will give borrowers the same return, which can be represented as

$$\hat{\pi} \equiv P(r)(v - r) = P(r_0)(v - r_0) \tag{6}$$

Note that $P(r)$ is the probability that a listing generates contributions from N investors before experiencing a death shock. Define $V(r, n)$ as the value function of a listing with rate r and progress n, then

$$V(r, n) = (1 - \delta dt - \eta p(r)dt)V(r, n) + \eta p(r)V(r, n + 1)$$

Rearrange the above dynamics and let $dt \to 0$; we have

$$V(r, n) = q(r)V(r, n + 1)$$

where

$$q(r) \equiv \frac{\eta p(r)}{\eta p(r) + \delta} \tag{7}$$

is the probability that a listing with rate r generates one more match without encountering a death shock. Specifically, because $V(r, N) = N(v - r)$ and $V(r, 0) = \hat{\pi}$, we have

$$P(r) = q(r)^N = \left(\frac{\eta p(r)}{\delta + \eta p(r)}\right)^N \tag{8}$$

In terms of the expression of $p(r)$, according to the setup, an investor randomly draws ℓ listings, each of which follows an i.i.d. distribution $G(r)$. Therefore, for any distribution of ℓ, we have

Lemma 3. *In the stationary equilibrium, given $G(r)$, $p(r)$ takes the form*

$$p(r) = \frac{\sum_\ell \ell \cdot \Pr(\ell) \cdot G(r)^{\ell-1}}{\mathbb{E}(\ell)} \tag{9}$$

which is increasing in r.

For the above result, note that while the unconditional probability of drawing ℓ listings is $\Pr(\ell)$, from a borrower's perspective, the probability that the met investor has ℓ listings in his sample is equal to $\Pr(\ell) \cdot \ell/\mathbb{E}(\ell)$, which places greater weight on larger realizations of ℓ. Based on the assumption that investors will choose the higher interest rate r, I show that $p(r)$ is increasing in r. By Equation (8), $P(r)$ is also increasing in r. To show that the decision rule is belief-consistent, I derive the analytic expression of $Q(r)$ in terms of $P(r)$ and $p(r)$ and show that it is also increasing in r.

Lemma 4. *$Q(r)$ takes the form*

$$Q(r) = \frac{1}{1-P(r)} \frac{N\delta}{\delta + \eta p(r)} \left(\frac{\eta p(r)}{\delta + \eta p(r)} \right)^{N-1} \tag{10}$$

which is increasing in r.

Hence, investor's expected utility

$$u(r) = Q(r)r + (1 - Q(r))r_0$$

is also increasing in r. Therefore:

Proposition 2. *That investors choose the highest rate in their sample is belief-consistent.*

To demonstrate the existence and uniqueness of a stationary equilibrium with mixed strategies under the belief-consistent assumption that investors always choose to invest in the listing with the highest rate, several intermediate results need to be shown. First, because the matching intensity $\eta p(r)$ is independent of progress n, the stationary equilibrium condition (Equation (4)) can be simplified to

Lemma 5.

$$\delta \mathcal{L} g(r) = L f(r)(1 - P(r)) \tag{11}$$

Intuitively, the LHS of the equation is the measure of dead projects in a unit of time, while the RHS of the equation describes the expected number of new inflows that will ultimately fail. In the stationary system, the equation must hold for all $r \in \mathbf{r}$. In addition, the above equation also implies that g and f have a monotone likelihood ratio, as $P(r)$ is increasing in r. That is, for any distribution inflow f, listings with a higher interest rate will be funded faster. By rearranging Equation (11) and integrating both sides with respect to r, I have

$$L = \delta \mathcal{L} \int_{r} \frac{g(r)}{1 - P(r)} dr$$

By Equation (8), this becomes

$$L = \delta \mathcal{L} \int_{r} \frac{1}{1 - \left(\frac{\eta p(r)}{\eta p(r) + \delta}\right)^{N}} dG(r)$$

According to Lemma 3, $p(r)$ is a function of $G(r)$; therefore, we can map the interest rate distribution $r \in [r_0, \bar{r}]$ to a measure with $x \in [0, 1]$. Together with Equation (3), I derive the condition to specify equilibrium meeting intensity η.

Lemma 6. *In the stationary equilibrium, η satisfies*

$$\frac{\delta}{\eta} \int_{0}^{1} \frac{1}{1 - \left(\frac{\eta \tilde{p}(x)}{\eta \tilde{p}(x) + \delta}\right)^{N}} dx = \frac{L}{I \mathbb{E}(\ell)} \tag{12}$$

where

$$\tilde{p}(x) \equiv \frac{\sum_{\ell} \ell \cdot \Pr(\ell) \cdot x^{\ell - 1}}{\mathbb{E}(\ell)} \tag{13}$$

Moreover, $\eta > 0$ exists and is uniquely determined.

The above result significantly simplifies our analysis because η is uniquely determined, which allows me to straightforwardly prove the existence and uniqueness of the stationary equilibrium in the many-to-one matching framework.

Theorem 1. *There is a unique stationary equilibrium in which investors choose the highest interest rate in their sample and borrowers implement identical mixed strategies.*

Proof. The logic behind the proof is also the algorithm for solving the problem numerically. Beginning from the unique η, we can solve all of the equilibrium elements according to the following steps.

$$(\eta, \mathcal{L}) \Rightarrow \hat{\pi} \Rightarrow (P(r), p(r)) \Rightarrow \{G(r), g(r)\} \Rightarrow \{F(r), f(r)\}$$

For the details of the proof, see the Appendix. □

3.4 Supply and Demand

Given existence and uniqueness, in this section, I discuss how equilibrium conditions respond to the market's state variables such as I, L and N. I will report several testable results that can be verified in the data. First result investigates how the meeting intensity η and market depth $\mathcal{L}$ are affected by the supply/demand ratio L/I and loan size N.

Proposition 3. *In the stationary equilibrium, (i) η is decreasing in L/I and N while $\mathcal{L}$ is increasing in L/I and N. (ii) η converges to $\delta I \mathbb{E}(\ell)/L$ as $N \to \infty$.*

Proof. First, by Lemma 6, we have

$$\rho \int_0^1 \frac{1}{1 - \left(\frac{\tilde{p}(x)}{\tilde{p}(x)+\rho}\right)^N} dx = \frac{L}{I\mathbb{E}(\ell)}$$

where $\rho \equiv \delta/\eta$. Then, monotonicity can be proven by the Implicit Function Theorem. The limit of η can be derived by applying Bernoulli's Inequality and the Squeeze Theorem. For details, see the Appendix. □

In the statement above, (i) shows that, as the L/I ratio increases, given the same death rate and search technology, more projects will accumulate in the market, implying a larger $\mathcal{L}$, which directly indicates a lower meeting intensity η. Similarly, when N increases, more time is required for a project to be funded. Therefore, $\mathcal{L}$ will be increasing in N while η

is decreasing in N. (ii) implies that when N is increasing, the market depth $\mathcal{L}$ will never diverge, and hence η will not diminish to zero. Based on Proposition 3, the next proposition shows how rate distribution is affected by market demand and supply.

Proposition 4. *Denote the stationary distribution by $G(r; I, L, N)$. For two pairs of market supply and demand $(I_1, L_1), (I_2, L_2)$, if $L_1/I_1 > L_2/I_2$*

$$G(r; I_1, L_1, N) \succeq_{FOSD} G(r; I_2, L_2, N)$$

Given L/I, if $N_1 > N_2$ then

$$G(r; I, L, N_1) \succeq_{FOSD} G(r; I, L, N_2)$$

and $\bar{r}$ is increasing in L/I and N.

Intuitively, both L/I and N measure the competitiveness on the borrower side. As the ratio or average loan size increase, borrowers face severer competition and hence will commit to overall higher interest rates, which gives us the FOSD result. Correspondingly, $\bar{r}$ will be increasing with L/I and N as well. Moreover, the proposition also implies that, as a second order effect, when $N \cdot L/I$ is small, nearly all listings can be funded, and hence the interest rate will be close to r_0. However, as the demand side expands, this rate will converge to v. Therefore, the standard deviation of the interest rate and demand/supply ratio should have an inverse U-shaped relationship. A numerical computation is reported in Figure 3. In addition, an immediate result of Proposition 3 is that that the death rate δ plays an insignificant role in determining rate distribution and profitability.

Corollary 1. *$G(r)$, $P(r)$ and $\hat{\pi}$ are independent of δ.*

Intuitively, when δ is large, η will be increased by the same magnitude. Although each listing's life-span become shorter, as the market becomes less competitive, the funding likelihood can compensate for the death risk and thereby hold the funding probability unchanged. In a stationary equilibrium, the borrower's strategy and profit will be remain the same and free of δ.

4 Welfare

In this section, I discuss the main finding of the paper, which concerns the efficiency problem in a many-to-one matching market caused by coordination. First, I state the main theoretical result. Then, I apply the model to the data and estimate the change in welfare difference between a dispersed price and random matching environment.

4.1 Rate Dispersion and Coordination

To begin, let us consider the special case in which $N = 1$. In this environment, each investor can finance a project alone. Therefore, the measure of successful listings at each unit of time is simply I. That is, the interest rate, regardless of being unified or dispersed, is simply a monetary transfer between the two sides. However, when $N > 1$, a listing cannot be fully funded by a single investor. Moreover, investors who have made an investment will be locked in with the listing and face a risk of failure; therefore, market welfare of the market could be affected. Market welfare can be expressed as

$$\mathcal{W} = L \int_r P(r) f(r) dr$$

which represents the expected number of listings that will ultimately be fully funded. By Equation (11), we have

$$\mathcal{W} = L - \delta \mathcal{L}$$

which is the difference between new inflows and dead listings at each moment. Hence, to compare efficiency levels across different search friction technologies, it is sufficient to compare equilibrium market sizes $\mathcal{L}$.

Theorem 2 (Efficiency)**.** *Given* (I, L, N)*, a market with* $\Pr(\ell = 1) \in (0, 1)$ *has a larger* $\mathcal{W}$ *than that with* $\Pr(\ell = 1) \in \{0, 1\}$*.*

Theorem 2 shows that, although a certain level of friction prevents investors from viewing all listings in the market, from a social perspective, under a many-to-one matching framework, friction improves welfare, measured by expected number of successfully funded projects, compared with the perfect competition case. The novel effect is induced by a mixture of dispersed price generated by search frictions and the lack of a coordination mechanism in the many-to-one environment. As discussed above, in a one-to-one matching market, there is no problem regarding coordination, hence interest rates simply determines how to divide surplus. However, in the many-to-one environment, if investors cannot observe listings' funding status and make their decisions independently, the interest rate is the unique information that helps them to make decisions. If there is no differentiation among projects, investors tend to chose which to invest in at random, which is no better than the case in which each investor can observe only one listing (the case $\ell \equiv 1$). However, under a certain level of search frictions, the most important feature generated here is the persistent rate dispersion that induces a mechanism for investors to sort the listings in their samples. In principle, listings with higher rates not only provide investors a potentially higher return but also serve as a signal that helps investors to coordinate. Such biased funding dynamics increase the overall number of fully funded projects, indicating enhanced social welfare. The general implications of the analysis shed light on mechanism design and information disclosure in such many-to-one matching environments in which the side of "one" posts the price, while the "many" side searches. It seems that in such a decentralized matching market, if there is no other effective coordination mechanism, price regulation or unifying the quality of the goods is harmful to market efficiency and perfect information disclosure might also be inefficient. Recall the simple example mentioned in the Introduction: suppose that there are two valuable projects, each of which requires two units of contribution. If there is a mechanism to differentiate the two projects, it would be easier for the two investors to contribute to the same one. In my model, rate dispersion represents such an endogenous property that improves coordination.

In general, the model applies to any two-sided market with increasing returns to scale. For instance, in the labor market for start-up companies, new firms enjoy increasing returns to scale in labor during their early stages. However, in general, adjusting hiring information such as wages is costly in the short run, and it is impossible for a firm to contract with workers based on how many employees it has hired. Therefore, if employers have perfect competition, then all of them will grow at the same pace and will reach optimal scale after a longer period. However, when the competition is imperfect and features wage dispersion, the endogenous sorting mechanism will cause some firms to reach optimal size earlier, which from the social perspective, is beneficial.

As a final remark on the theoretical analysis, one may be interested in the case in which, if there is exogenous coordination in the market, would price dispersion be beneficial? For instance, if listing progress is perfectly observable, will rate dispersion coordinate or distort it? Intuitively, the answer would be the latter. Intuitively, given rate dispersion, one possible situation is that one investor will invest his money in a project with a high rate and low progress, bypassing other projects with low rates and high progress in his sample, which violates the socially optimal allocation rule, under which more advanced projects should always have priority to be matched. If so, eliminating product differentiation, such as by unifying the interest rate, could act as a effective regulation to improve welfare.

4.2 Estimation

4.2.1 Estimation Strategy

The theoretical analysis of the paper shows that when a many-to-one matching market lacks a coordination mechanism, price dispersion induced by search frictions could reduce welfare loss. The expected number of fully funded projects, which measures matching efficiency, will increase. In this section, we attempt to quantitatively estimate the efficiency gain due to rate dispersion by introducing a straightforward method to measure search cost primitives. Specifically, we compute the ratio of welfare under random matching to that under dispersed rates, denoted as

$$w \equiv \frac{\mathcal{W}_{\text{Random Matching}}}{\mathcal{W}_{\text{Dispersed Price}}}$$

As shown in Theorem 2, the ratio has to be no greater than one. To estimate the welfare difference, first, we show that it is sufficient to identify and estimate the following function

Proposition 5. *Define*

$$H(x) \equiv \tilde{p}(x) \cdot \mathbb{E}(\ell)$$

where $x \in [0, 1]$ is a sufficient statistic to estimate w.

The proposition implies that to estimate the welfare ratio, I need not know the absolute level of rate dispersion. Instead, an estimation based on percentile data is sufficient. The result is directly implied by Lemma 6. In the expression, the only unknown is η; L, I, N are observable in the data. Suppose that $H(x)$ is known, as $\tilde{p}(1) = 1$, $\mathbb{E}(\ell)$ is achieved. Further, the whole function of $\tilde{p}(x)$ is known. Accordingly, η can be uniquely solved, by $\mathcal{L}$. By that

$$\mathcal{W} = L - \delta \mathcal{L}$$

I am able to compute welfare directly. To identify and estimate H, we have the following result.

Proposition 6. *Given (N, I, L), $H(x)$ can be computed by*

$$H(x) = \frac{P(x; z, N)^{1/N}}{1 - P(x; z, N)^{1/N}} \frac{z}{\int_0^1 \frac{dx}{1 - P(x, z; N)}} \tag{14}$$

where $z \equiv L/I$ and $P(x; z, N)$ is the funding probability of project at the x percentile.

In the RHS of the expression, $z = L/I$ and N are observable, while $P(x; z, N)$ can be non-parametrically estimated by computing the average probability of funding at each percentile. Moreover, the proposition simplifies the estimation by avoiding the need to identify of r_0 and v, which might be determined by some unobservable elements such as the change in the platform's systematic risk and variables external to the market. Given $H(x)$, I describe my estimation strategy as follows.

1. Separate the data into four-hour intervals.[13]

2. Compute $z_t = L_t / I_t$

3. Compute average number of investments per listing, denoted N_t.

[13] The selection of 4 hours reflects a trade-off between sample size and market volatility. In principle, the longer the time intervals, the larger the sample in each group, meaning that I can compute P more precisely. However, as supply and demand may vary over time, we need to keep the time interval shorter to maintain the stationary assumption.

4. For each t with the same I_t, L_t and N_t, compute the average funding probability $P(x; z, N)$ by choosing proper grid for x.[14]

5. Compute $H(x)$ according to Equation (14)

4.2.2 Result

Table 13 and 14 report the estimated result of $H(x)$ based on grids with the 10th and 25 percentile, respectively. Figure 5 graphically illustrates the function. Note that in the expression of $H(x)$, $H(0)$ is equal to $\Pr(\ell = 1)$, while $H(1)$ is the estimate of $\mathbb{E}(\ell)$. According to the estimates, on average, approximately 35% of investors enter the market by only looking at one listing. On average, the number of listings observed by each investor is approximately 1.76. The reported number implies that, although the number of listings in the platform seems to be large, each investor's effective observation is quite limited. In a behavioral interpretation, there could be a significant level of idiosyncratic randomness associated with investors' decision making, which gives borrowers some market power and leads to dispersed interest rates. Next, I use the estimated $H(x)$ to compute the welfare ratio w under different combinations of N and L/I, and the result is shown in Figure 6. According to the graph, when $NL < I$, there will be no welfare loss between the dispersed price and random matching cases because $\mathcal{L} = 0$ in either case. Moreover, when $N = 1$, the ratio is equal to 1. According to our data, the $N \cdot L/I$ ratio is approximately 1.8 on average, while the average N is approximately equal to 6. According to the calibration, $w = 0.7807$. That is, with a dispersed rate as a coordination mechanism, the approximate welfare gain could be approximately 28.09%

5 Endogenous Sizes

In this section, we study a simple extension of the model such that loan size is another choice variable. For simplicity, and without loss of generality, I assume that the choice of size can be either 1 or 2. All the other elements such as investors' search technology $\Pr(\ell)$,

[14] Although we have approximately 250,000 observations in the sample, conducting kernel estimation requires a high dimension of x; therefore, in our result, I only use the 10th and 25th percentiles.

the random death rate δ and market supply and demand (L, I) remain the same. In terms of investors' information set, assume that they are able to observe a project's rate and size. However, for a project of size 2, progress is still unobservable.

5.1 Return Equivalence

Note that because the sizes of the loans in an investor's sample could differ, it is necessary to characterize investors' return equivalent conditions among listings with different sizes. Denote $p_n(r)$ as the probability that a listing of size n and rate r will be invested in conditional on being viewed. Correspondingly, define $q_n(r) \equiv \frac{\eta p_n(r)}{\eta p_n(r)+\delta}$. By Equation (10), if an investor invests in a project with $(r_1, 1)$, the return is simply r_1. For a project with $(r_2, 2)$, then the expected return will be

$$\frac{2q_2(r_2)}{1+q_2(r_2)}r_2 + \frac{1-q_2(r_2)}{1+q_2(r_2)}r_0$$

Hence, the return equivalence relationship between $(r_1, 1)$ and $(r_2, 2)$ is as follows

$$r_1(r_2) = \frac{2q_2(r_2)}{1+q_2(r_2)}r_2 + \frac{1-q_2(r_2)}{1+q_2(r_2)}r_0 \tag{15a}$$

Intuitively, given a project of size two, investors require a higher rate to compensate for the risk of failure. Moreover, note that when the two projects are return-equivalent to investors, this implies that $p_1(r_1) = p_2(r_2)$, so do $q_i(r_i)$. Therefore, the above equation can be also represented by

$$r_2(r_1) = \frac{1+q_1(r_1)}{2q_1(r_1)}r_1 - \frac{1-q_1(r_1)}{2q_1(r_1)}r_0 \tag{15b}$$

5.2 Equilibrium Characterization

To begin, let us consider two extreme cases. First, when $\Pr(\ell = 1) = 1$, the unique equilibrium is that all borrowers will choose $r = r_0$. Second, when $\Pr(\ell > 1) = 1$, the result is that all listings are of identical size and rate $(r, n) = (v, 1)$. When Assumption 3 holds, the following lemma describes the conditions for two listing sizes to co-exist in the market.

Lemma 7. *If $\frac{L}{I} \geq 1 + \Pr(\ell = 1)$, all borrowers will choose to issue loans of size one. If*

$\frac{L}{I} < z^*$ *for some* $z^* \in (0, 1 + \Pr(\ell = 1))$*, then all borrowers will choose to issue loans of size two.*

Intuitively, there are two forces that determine borrowers' loan sizes. First, when the borrower/investor ratio is higher, the borrower side will be more competitive. Then, borrowers will tend to request smaller loans to increase the likelihood of being funded. Another force is the probability that $\ell = 1$, which represents the level of search friction. When friction is high, it is more likely to generate support for all projects, and hence the larger projects are more easily funded. As stated in Lemma 7, when the first effect dominates the latter, only smaller loans exist in the market. However, if L/I is small enough, all the borrowers will issue larger loans because there are enough investors flowing into the market. In an extreme case, when $L/I = 0.5$, then even if all borrowers choose size 2, the funding probability is always one. In the intermediate cases, the two sizes may co-exist in the market and all borrowers would then generate the same expected profit.

For the remainder of the section, we assume that $\frac{L}{I} \in (z^*, 1 + \Pr(\ell = 1))$, which guarantees the co-existence of the two types of projects. Denote the rate distribution chosen by borrowers by

$$\{F_1(r), f_1(r)\}, \{F_2(r), f_2(r)\}$$

and stationary rate distribution by

$$\{G_1(r), g_1(r)\}, \{G_2(r), g_2(r)\}$$

First, it is trivial that the lowest rate in equilibrium would be r_0. In addition, denote $\mathcal{L}_1$ and $\mathcal{L}_2$ as the measure of listings of size 1 and 2, respectively. Further note that in equilibrium, it must be the case that two types of the projects are of equal profit $\hat{\pi}_2 = \hat{\pi}_1$. Denote $\mathbf{r}_i$ as the support of listings with size i. The first property we will describe below is that the strategy set is disjoint between two types in any equilibrium. Formally,

Lemma 8. *In any equilibrium in which* $\mathbf{r}_i \neq \emptyset$*, there exists only one pair of* (r_1, r_2) *that satisfies the following two conditions simultaneously.*

- *Return Equivalence:* $(r_1, 1) \sim (r_2, 2)$

- *On-Path:* $r_i \in \mathbf{r}_i$ *for* $i = 1, 2$

As there is only one pair of rates (r_1, r_2) that makes investors indifferent in equilibrium, it seems natural to ask which type is relatively more preferable to them. The upper bound of the less-preferred type's strategy set should be indifferent to the lower bound of the more-preferred type's strategy set. The less preferred type has the lowest rate at r_0. The following proposition claims that larger projects should be preferred to smaller projects in equilibrium because larger borrowers are willing to offer much higher interest rates to investors.

Proposition 7. *In equilibrium, larger projects have higher interest rates. Specifically,* $r_1 \in [r_0, \bar{r}_1]$*, while* $r_2 \in [\underline{r}_2, \bar{r}_2]$ *such that*

$$(\bar{r}_1, 1) \sim (\underline{r}_2, 2)$$

Proof. As indicated in Lemma 8, there exists only one pair of (r_1, r_2) that satisfies *Return Equivalence* and *On-Path*, which implies that $\mathbf{r}_1$ and $\mathbf{r}_2$ are two disjoint intervals. Furthermore, it is obvious that there is no utility gap for investors. Otherwise, all borrowers would have an incentive to fill the gap, which is a profitable deviation. Hence, in equilibrium, there are only two possible cases.

- Case 1. Larger projects have higher rates
- Case 2. Smaller projects have higher rates

The detail of the proof is shown in the Appendix □

Proposition 7 implies that, comparatively, when loans could be of heterogeneous sizes, borrowers tend to offer higher interest rates for larger loans to compensate for the risk of failure. Specifically, when loans are of different sizes, the interest rates are distributed in disjoint ranges. Even if investors are concerned about both the return r and expected funding probability, in equilibrium, monotonicity guarantees that the interest rate is the dominant factor taken into consideration.

6 Conclusion

This paper studies, theoretically and empirically, how search frictions affect price competition and allocation efficiency in a many-to-one matching market. Motivated by the significant mismatch and persistent price dispersion observed in an online crowdfunding market, I argue that search frictions faced by investors play an important role in affecting borrowers' pricing behavior.

The key feature that distinguishes my work from classical search models is that borrower must attract many investors, and so investors must coordinate which projects to fund. The surprising finding of the paper is that a certain level of search frictions can fix the coordination problem by creating ex post heterogeneity. Hence, given a fixed inflow of external funding, the number of funded projects will increase due to the joint effect of the two types of frictions.

More generally, my work provides a tractable framework to study competition behaviors in crowdfunding markets, while majority of the existing models restrain the borrower as a monopolist. There are several interesting ways to extend the model to capture additional important aspects of the market. For instance, in this paper, I only focus on debt-based crowdfunding. By modifying agents' payoffs, one could apply the model to other types of platforms such as crowdfunding markets that are equity based, presale based, and so on.

Moreover, I hope that my model can be extended and applied to other fields. In fact, the many-to-one feature of crowdfunding is an extreme case of an economy with increasing return to scale. The property is shared by many other scenarios, such as forming social networks, producing public goods, and recruiting employees at firms' early stages. My model provides two insights of these markets. First, an increasing return to scale market prefers unbalanced growth, which can be facilitated by heterogeneity among competitors. Second, if there is no exogenous heterogeneity, information imperfections such as search frictions can help to generate one.

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Appendix A. Additional Empirical Evidence

To assess the validity of the model, I document several additional empirical facts. Specifically, I focus on the average interest rate level, dispersion level and their correlation across observable state variables.

First, our model predicts that given constant (L, I, N), aggregate rate dispersion is the result of borrowers' strategies. However in the long run, as demand and supply are fluctuating over time, rate dispersion should correspond to variations in the state variables. I compare rate dispersion across different time horizons. According to Table 7, I find

Fact 3. *Rate dispersion is increasing in the time horizon.*

According to Table 7, the overall dispersion (0.6756%) is twice that of hourly dispersion (0.3403%). Moreover, I compute the same statistics for successful listings alone. The table reports that the rate dispersion of successful loans is relatively low compared with statistics corresponding to all listings. However, the two numbers converge as the time horizon increases.

Fact 4. *As the time horizon increases, the difference in dispersion between all and successful listings declines.*

While the hourly dispersion is of approximately 3 times lower (0.3403% vs 0.1268%), the overall dispersion is nearly identical (0.6756% vs 0.6218%) between whole sample and successful listings. The facts confirm our model prediction, which suggests that in the short run, price dispersion is due to individual-level dispersion. However in the long run, dispersion would correspond to fluctuations in the market's state variables such as supply and demand.

The next set of tests attempts to compare the average rate and dispersion under different levels of demand and supply. According to Proposition 4, when L/I increases, the rate distribution will FOSD the distribution with a lower L/I ratio. This implies that the mean of interest rates should be increasing in L and decreasing in I. As reported in Table 9, we have

Fact 5. *The average rate level is positively correlated with funding demand and negatively correlated with funding supply.*

As for rate dispersion, when L/I is small, the rate will degenerate to r_0; when L/I increases, rate will converge to v as the market becomes more competitive. Therefore, the second moment of interest rates should demonstrate an inverse U-shaped relationship with $z = L/I$. Therefore, I run a regression w.r.t the JNS measure of the rate dispersion level, again z and z^2, controlling for other observable variables. As reported in Table 10, under the hourly measure, the pattern is significant. However, in the regression using daily averages, as demand and supply fluctuate within a day in the market, the pattern disappears.

Fact 6. *There is an inverse U-shaped relationship between rate dispersion and the supply/demand ratio (as measured by $z = L/I$).*

The last two facts concern the size effect in the crowdfunding market. According to the analysis in Section 6, when L/I increases, N decreases on average. Consistent with the model prediction, according to Table 12,

Fact 7. *Average loan size is negatively correlated with the number of listings and positively correlated with the number of investors.*

Finally, I compare interest rates across listings with different sizes during the same period by estimating a random effects model controlling for aggregate variables during that period. As reported in Table 11, there is a significant and positive correlation between sizes and rates. Consistent with our theoretical analysis, when size is another choice variable available to fundraisers, they will offer a higher rate to compensate for the size of their requests.

Fact 8. *Rate and size are positively correlated.*

Appendix B. Proofs

Proof of Lemma 2

In a symmetric equilibrium with continuous mixed strategy $\{F(r), f(r)\}$, suppose $\underline{r} > r_0$. When a borrower's rate $r = \underline{r}$, then the listing must be the least attractive one on any investor's sample. Hence, the only possibility of being invested is that the investor's sample size $\ell = 1$. If so, every borrowers has incentive to lower the $\underline{r}$, which will not affect funding probability but will increase profit conditional on fully funded. $\square$

Proof of Lemma 3

In stationary equilibrium, the measure of projects that are matched should be balanced on both sides for each rate $r \in \mathbf{r}$, i.e.

$$I \cdot \Pr(r_{invest} \leq r) = \eta\mathcal{L} \cdot \Pr(r_{fund} \leq r)$$

The LHS is the total measure of investors whose invested project is below r, while the RHS represents the listings who make a unit of progress and have rates no larger than r. The LHS can be represented as

$$I \cdot \Pr(r_{invest} \leq r) = I \cdot \sum_{\ell} \Pr(\ell) \cdot G(r)^{\ell}$$

For an investor, for each realization of ℓ, the probability that the best rate is less than r is $G(r)^{\ell}$. However, the measure of projects with rate less than r and make one step further can be represented as

$$\Pr(r_{fund} \leq r) = \int_{r_0}^{r} g(z)p(z)dz$$

Take the derivative of the above two expressions w.r.t. r, then we have

$$I \cdot g(r) \sum_{\ell} \ell \cdot \Pr(\ell) \cdot G(r)^{\ell-1} = \eta\mathcal{L} \cdot g(r)p(r)$$

Moreover, by Equation (3), we have the desired result. $\square$

Proof of Lemma 4

When an investor observes a project with rate r, he has to infer the distribution of the project's progress distribution. First, provided that the project is still listed, its age distribution is exponential with parameter δ. Hence, the probability that the progress is equal to n can be expressed as

$$\int_0^\infty \delta e^{-\delta t} \cdot \frac{e^{-\eta p(r)t}(\eta p(r)t)^n}{n!} dt$$

which is equal to

$$\frac{1}{1-P(r)} \frac{\delta(\eta p(r))^n}{(\delta+\eta p(r))^{n+1}}$$

Given n, the probability that the project can reach N before death is

$$\left(\frac{\eta p(r)}{\delta+\eta p(r)}\right)^{N-n-1}$$

Therefore, the expected probability is equal to

$$\frac{1}{1-P(r)} \sum_{n=0}^{N-1} \frac{\delta(\eta p(r))^n}{(\delta+\eta p(r))^{n+1}} \left(\frac{\eta p(r)}{\delta+\eta p(r)}\right)^{N-n-1}$$

which gives us

$$Q(r) = \frac{1}{1-P(r)} \frac{N\delta}{\delta+\eta p(r)} \left(\frac{\eta p(r)}{\delta+\eta p(r)}\right)^{N-1}$$

To show that $Q(r)$ is increasing in r, by the expression of $P(r)$, we have

$$Q(r) = \left(\sum_{n=0}^{N-1} \left(\frac{\eta p(r)}{\delta+\eta p(r)}\right)^n\right)^{-1} \left(\frac{\eta p(r)}{\delta+\eta p(r)}\right)^{N-1} = \sum_{n=1}^{N-1} \left(\frac{1}{q(r)^n}\right)^{-1}$$

As $q(r)$ is increasing in r, $Q(r)$ is also increasing.

□

Proof of Lemma 5

By stationary conditions (Equation (4)), we have

$$g(r,n) = g(r,n-1) \cdot \frac{\eta p(r)}{\eta p(r)+\delta}$$

for all $n \in \{1, 2...N-1\}$. In addition, we know that

$$g(r) = \sum_{n=0}^{N-1} g(r, n)$$

hence we have

$$\mathcal{L}g(r, N-1) = \mathcal{L}g(r, 0) \cdot \left(\frac{\eta p(r)}{\eta p(r) + \delta}\right)^{N-1} = \frac{Lf(r)}{\eta p(r) + \delta} \cdot \left(\frac{\eta p(r)}{\eta p(r) + \delta}\right)^{N-1}$$

and by

$$Lf(r) = \mathcal{L} \cdot (\delta \cdot g(r) + \eta p(r) \cdot g(r, N-1))$$

and Equation (8), we have

$$Lf(r) = \mathcal{L} \cdot \delta g(r) + Lf(r)P(r)$$

$\square$

Proof of Lemma 6

By Equation (11) and Equation (8), we have

$$L = \delta\mathcal{L} \int_{r \in \mathbf{r}} \frac{1}{1 - \left(\frac{\eta p(r)}{\eta p(r) + \delta}\right)^N} dG(r)$$

Note that $G(r)$ is continuous with domain $[0, 1]$. Moreover, by Lemma 3, $p(r)$ can be represented as $p(G(r))$, which implies that p is a function of G. Therefore, we can define $\tilde{p}(x)$ as in Equation (13) and obtain Equation (12). To show that there exists a unique η that solves the problem, define

$$\mathcal{F}(\rho) = \rho \int_0^1 \frac{1}{1 - \left(\frac{\tilde{p}(x)}{\tilde{p}(x) + \rho}\right)^N} dx - \frac{L}{I\mathbb{E}(\ell)}$$

where $\rho \equiv \delta/\eta$. First, we show that $\mathcal{F}$ is monotone in ρ.

$$\frac{\partial \mathcal{F}}{\partial \rho} = \int_0^1 \frac{1}{1 - \left(\frac{\tilde{p}(x)}{\tilde{p}(x) + \rho}\right)^N} dx - \rho \int_0^1 \frac{N\left(\frac{\tilde{p}(x)}{\tilde{p}(x) + \rho}\right)^{N-1}}{\left(1 - \left(\frac{\tilde{p}(x)}{\tilde{p}(x) + \rho}\right)^N\right)^2} \frac{\tilde{p}(x)}{(\tilde{p}(x) + \rho)^2} dx$$

For simplicity, denote $\tilde{q}(x) \equiv \frac{p(x)}{(\tilde{p}(x)+\rho)}$, then the above partial derivative equals

$$\int_0^1 \frac{1}{1-\tilde{q}(x)^N} dx - \int_0^1 \frac{N\tilde{q}(x)^{N-1}}{(1-\tilde{q}(x)^N)^2} \tilde{q}(x)(1-\tilde{q}(x)) dx$$

To show that the term is positive, it is sufficient to show that the integrand is always positive, or equivalently

$$1-\tilde{q}(x)^N - N\tilde{q}(x)^N(1-\tilde{q}(x)) > 0$$

It is easy to show that, first, the term is decreasing in $q(x)$; second, when $\tilde{q}(x) = 0, 1$, the above term equals 1, 0, respectively. As $\tilde{q}(x) \in (0, 1)$, the above term is positive universally. Therefore, $\mathcal{F}$ is increasing in ρ and hence is decreasing in η. To demonstrate the existence and uniqueness of η, I rewrite the above equation as

$$\mathcal{F}(\rho) = \int_0^1 \frac{\tilde{p}(x)+\rho}{\sum_{n=0}^N \left(\frac{\tilde{p}(x)}{\tilde{p}(x)+\rho}\right)^n} dx - \frac{L}{I\mathbb{E}(\ell)}$$

When $\rho = 0$, the above equation becomes

$$\mathcal{F}(0) = \frac{1}{(N+1)\mathbb{E}(\ell)} - \frac{L}{I\mathbb{E}(\ell)}$$

By Assumption 2, the above term is negative. When ρ goes to infinity, $\mathcal{F}(0)$ will also go to infinity. By the Intermediate Value Theorem, there is a ρ such that $\mathcal{F}(\rho) = 0$. Because $\mathcal{F}(\rho)$ is increasing in ρ, the solution is unique. Therefore, η is uniquely determined. □

Proof of Theorem 1

Because η is uniquely determined, $\mathcal{L}$ is also uniquely determined. Because the lower bound of the borrowers' mixed strategy is always r_0, in equilibrium, the indifference condition implies that

$$\hat{\pi} = P(r_0) \cdot N(v - r_0)$$

where

$$P(r_0) = \left(\frac{\eta p(r_0)}{\delta + \eta p(r_0)}\right)^N$$

Note that $G(r_0) = 0$; therefore, $p(r_0) = \tilde{p}(0)$. Therefore, $P(r_0)$ is uniquely specified, as is $\hat{\pi}$. In the next step, provided that the equilibrium profit is uniquely determined, we have

$$P(r) = \frac{\hat{\pi}}{v - r}$$

So

$$p(r) = \frac{\delta}{\eta} \frac{\left(\frac{\hat{\pi}}{v-r}\right)^{1/N}}{1 - \left(\frac{\hat{\pi}}{v-r}\right)^{1/N}}$$

is uniquely determined. By Lemma 3, I find unique $G(r)$ and $g(r)$. Finally, $f(r) = \frac{\delta \mathcal{L} g(r)}{L(1-P(r))}$ is unique. In summary, beginning from the existence and uniqueness of η, all equilibrium elements of the equilibrium can be derived step by step. □

Proof of Proposition 3

The monotonicity can be proven by the Implicit Function Theorem. Thus, the limit of η can be derived by applying Bernoulli's Inequality and, immediately, the Squeeze Theorem.

(i) Monotonicity

By Lemma 6, we have

$$\frac{\delta}{\eta} \int_0^1 \frac{1}{1 - \left(\frac{\tilde{p}(x)}{\tilde{p}(x)+\frac{\delta}{\eta}}\right)^N} dx = \frac{L}{I\mathbb{E}(\ell)}$$

Define $\rho \equiv \delta/\eta$ and $z \equiv L/I$, and hence

$$\mathcal{F}(\rho, N, z) \equiv \rho \int_0^1 \frac{1}{1 - \left(\frac{\tilde{p}(x)}{\tilde{p}(x)+\rho}\right)^N} dx - \frac{z}{\mathbb{E}(\ell)}$$

Obviously, both $\partial\mathcal{F}/\partial N$ and $\partial\mathcal{F}/\partial z$ are negative. For $\partial F/\partial \rho$, we have shown in the proof of Lemma 6 that $\partial\mathcal{F}/\partial\rho$. By the Implicit Function Theorem, we have

$$\frac{d\rho}{dN} = -\frac{\partial\mathcal{F}/\partial N}{\partial\mathcal{F}/\partial\rho} > 0$$

and

$$\frac{d\rho}{dz} = -\frac{\partial\mathcal{F}/\partial z}{\partial\mathcal{F}/\partial\rho} > 0$$

Therefore, ρ is increasing in both N and z, which implies that η is decreasing in N and z.

Moreover, by Equation (3), $\mathcal{L}$ is increasing in N and z. By $\rho = \delta/\eta$, we conclude that η is decreasing in N and $\mathcal{L}$ is increasing in N.

(ii) Limit

To find the limit of η, first, it is obvious that

$$\frac{L}{I\mathbb{E}(\ell)} \leq \rho$$

However,

$$\left(\frac{\tilde{p}(x)+\rho}{p(x)}\right)^N = \left(1+\frac{\rho}{\tilde{p}(x)}\right)^N > 1 + \frac{N\rho}{\tilde{p}(x)}$$

which is guaranteed by Bernoulli's Inequality. Therefore,

$$\begin{aligned}\frac{L}{I\mathbb{E}(\ell)} &= \rho \int_0^1 \frac{1}{1-\left(\frac{\tilde{p}(x)}{\tilde{p}(x)+\rho}\right)^N} dx \\ &< \rho \int_0^1 \frac{1}{\frac{N\rho}{N\rho+\tilde{p}(x)}} \\ &= \frac{1}{N}\int_0^1 \tilde{p}(x)dx + \rho\end{aligned}$$

Therefore, we have

$$\frac{L}{I\mathbb{E}(\ell)} > \rho > \frac{L}{I\mathbb{E}(\ell)} - \frac{1}{N}\int_0^1 \tilde{p}(x)dx$$

By the Squeeze Theorem, ρ converges to $\frac{L}{I\mathbb{E}(\ell)}$ as N goes to infinity. Thus, η converges to $\delta I\mathbb{E}(\ell)/L$.

$\square$

Proof of Proposition 4

By Lemma 3, as $p(r)$ and $G(r)$ are bijective, comparing $G(r; L, I, N)$ is equivalent to comparing $p(r)$ under different (N, I, L). Recall that

$$p(r) = \frac{\delta}{\eta}\frac{\left(\frac{\hat{\pi}}{v-r}\right)^{1/N}}{1-\left(\frac{\hat{\pi}}{v-r}\right)^{1/N}}$$

Let $\rho \equiv \delta/\eta$ and write $\hat{\pi} = P(r_0)(v - r_0)$. Then, we have

$$p(r) = \rho \cdot \frac{\frac{p(r_0)}{\rho + p(r_0)} \left(\frac{v - r_0}{v - r} \right)^{1/N}}{1 - \frac{p(r_0)}{\rho + p(r_0)} \left(\frac{v - r_0}{v - r} \right)^{1/N}}$$

By Proposition 3, it is easy to show that $p(r)$ is decreasing in L/I and N, as is $G(r)$. In terms of $\bar{r}$, because $p(r)$ is decreasing in L/I and N, while $\tilde{p}(x)$ is fixed with $\tilde{p}(1) = 1$, then we have that $\bar{r}$ is increasing in L/I and N. □

Proof of Theorem 2

The proof consists of two steps. In step one, we compare two cases by fixing the search technology. In the first case, we assume that fundraisers are free to set their rates. In the second case, we assume that the market imposes a price regulation such that all listings have to set a rate of r^*. In step two, we will show that for any search technology, a unique price will result in same level of social welfare.

Step One When borrowers are free to set their prices, when $\Pr(\ell = 1) \in (0, 1)$, as mentioned in the proof of Proposition 3

$$\int_0^1 \frac{\rho}{1 - \left(\frac{\tilde{p}(x)}{\tilde{p}(x) + \rho} \right)^N} dx = \frac{L}{I\mathbb{E}(\ell)}$$

where $\rho = \delta/\eta$. However, when the price regulation is imposed, then for each meeting, the probability that the project will be invested in is

$$p^* = \frac{\sum_\ell \Pr(\ell) \cdot \ell \cdot \frac{1}{\ell}}{\mathbb{E}(\ell)} = \frac{1}{\mathbb{E}(\ell)}$$

Further, note that in this case, all projects' funding probability is

$$P^* = \left(\frac{p^*}{p^* + \rho^*} \right)^N$$

where $\rho^* = \delta/\eta^*$. Hence, we have

$$\frac{\rho^*}{1 - \left(\frac{p^*}{p^* + \rho^*} \right)^N} = \frac{L}{I\mathbb{E}(\ell)}$$

By Equation (9),

$$\int_0^1 \tilde{p}(x)dx = \int_{r\in\mathbf{r}} p(r)dG(r) = \frac{1}{\mathbb{E}(\ell)}$$

Therefore, for any $\rho > 0$, Function

$$h(z,\rho) \equiv \frac{\rho}{1-\left(\frac{z}{z+\rho}\right)^N}$$

is convex in z, and strictly convex when $N > 1$, by Jensen's Inequality, we have

$$\int_0^1 \frac{\rho}{1-\left(\frac{p(x)}{p(x)+\rho}\right)^N} dx \le \frac{\rho}{1-\left(\frac{p^*}{p^*+\rho}\right)^N}$$

Moreover, "$\le$" takes "$=$" if and only if $N = 1$. As has already been shown, $h(z,\rho)$ is increasing in ρ, to have

$$\int_0^1 \frac{\rho}{1-\left(\frac{\tilde{p}(x)}{\tilde{p}(x)+\rho}\right)^N} dx = \frac{\rho^*}{1-\left(\frac{p^*}{p^*+\rho^*}\right)^N} = \frac{1}{\mathbb{E}(\ell)}$$

We have $\rho^* \ge \rho$ or $\eta^* \le \eta$, which indicates that

$$\mathcal{L}^* \ge \mathcal{L}$$

Step Two To show that for any search technology, when there is no rate dispersion, $\mathcal{L}$ remains constant. Suppose that there is no rate dispersion, we have

$$p^* = \frac{1}{\mathbb{E}(\ell)}$$

Moreover, $\eta\mathcal{L} = \mathbb{E}(\ell)I$, a project's success rate is always

$$P^* = \left(\frac{\eta p^*}{\eta p^* + \delta}\right)^N = \left(\frac{I}{I+\delta\mathcal{L}}\right)^N$$

In the market, we have

$$\delta\mathcal{L} = L(1-P^*) = L - L\cdot\left(\frac{I}{I+\delta\mathcal{L}}\right)^N$$

which indicates that $\mathcal{L}$ is uniquely determined regardless of search technology. $\square$

Proof of Proposition 5

First, we have

$$\mathcal{W}_{\text{Dispersed Price}} = L - \delta\mathcal{L} = L - \frac{\delta}{\eta}\mathbb{E}(\ell)I$$

Therefore,

$$\frac{\mathcal{W}_{\text{Dispersed Price}}}{\mathcal{W}_{\text{random matching}}} = \frac{L - \frac{\delta}{\eta}\mathbb{E}(\ell)I}{L - \frac{\delta}{\eta^*}\mathbb{E}(\ell)I}$$

By Lemma 6, η solves

$$\frac{\delta}{\eta}\int_0^1 \frac{1}{1-\left(\frac{\eta\tilde{p}(x)}{\tilde{\eta}p(x)+\delta}\right)^N}dx = \frac{L}{I\mathbb{E}(\ell)}$$

which implies that $\tilde{p}$ is a sufficient static to η. Meanwhile, as shown in the proof of Theorem 2, η^* solves

$$\frac{\delta}{\eta^*}\frac{1}{1-\left(\frac{\eta^* p^*}{\eta^* p^*+\delta}\right)^N} = \frac{1}{\mathbb{E}(\ell)}$$

where $p^* = \frac{1}{\mathbb{E}(\ell)}$. Thus, $\mathbb{E}(\ell)$ is sufficient for η^*. In $H(x) \equiv \tilde{p}(x)\mathbb{E}(\ell)$, by $\tilde{p}(1) = 1$, we have $H(1) = \mathbb{E}(\ell)$, and hence $\tilde{p}(x) = H(x)/H(1)$. □

Proof of Proposition 6

Because

$$P(x) = \left(\frac{\eta\tilde{p}(x)}{\eta\tilde{p}(x)+\delta}\right)^N$$

we have

$$\tilde{p}(x) = \frac{\delta}{\eta}\frac{P(x)^{1/N}}{1-P(x)^{1/N}}$$

Equation (3), we have

$$H(x) \equiv \tilde{p}(x)\mathbb{E}(\ell) = \frac{\eta\mathcal{L}}{I}\cdot\frac{\delta}{\eta}\cdot\frac{P(x)^{1/N}}{1-P(x)^{1/N}}.$$

In terms of $\delta\mathcal{L}$, by Equation (11), we have

$$\delta\mathcal{L} = \int_0^1 \frac{1}{1-P(x)}dx$$

□

Proof of Lemma 7

Given that all borrowers choose a loan of size one, we need to show that no one has an incentive to deviate to size two under any interest rate. Assume the opposite; suppose that there exists a profitable deviation $(r', 2)$. Then, by Equation (15b), it has to be the case that

$$r' \in [r_0, r_2(\bar{r})]$$

Moreover, denote $r = r_1(r')$, and the profit is equal to

$$2q_2(r')^2(v - r') = 2q_1(r)^2(v - r_2(r))$$

by Equation (15b), and hence profitable deviation implies that

$$q_1(r)(v - r) - (1 - q_1(r))(v - r_0) > 0$$

By the indifference condition, we have

$$1 - \frac{1 - q_1(r)}{q_1(r_0)} > 0$$

Because $q_1(\cdot)$ is increasing, profitable deviation exists if and only if

$$1 - \frac{1 - q_1(r_0)}{q_1(r_0)} > 0 \Leftrightarrow q_1(r_0) > \frac{1}{2}$$

According to the analysis of the one-to-one model, the above inequality implies that all borrowers will issue loans of size one if and only if

$$\frac{L}{I} \geq 1 + \Pr(\ell = 0)$$

□

Proof of Lemma 8

For *Return Equivalence*, as

$$r_1 = \frac{2q_2(r_2)}{1 + q_2(r_2)} r_2 + \frac{1 - q_2(r_2)}{1 + q_2(r_2)} r_0$$

and

$$q_2(r) = \frac{\eta p_2(r)}{\eta p_2(r) + \delta}$$

we have

$$p_2(r_2) = \frac{\delta}{\eta} \frac{r_1 - r_0}{2(r_2 - r_1)} \tag{16}$$

Moreover, if (r_n, n) is *On-Path*, it must be the case that

$$\hat{\pi}_n = n q_n(r_n)^n (v - r_n) = \left(\frac{\eta p_n(r_n)}{\eta p_n(r_n) + \delta} \right)^n n(v - r_n)$$

for $n = 1, 2$. In addition, as $p_1(r_1) = p_2(r_2)$, denoted $p^*(r_1, r_2)$, we have

$$\begin{aligned} p^*(r_1, r_2) &= \frac{\delta}{\eta} \frac{r_1 - r_0}{2(r_2 - r_1)} \\ &= \frac{\delta}{\eta} \frac{\hat{\pi}_1}{v - r_1 - \hat{\pi}_1} \\ &= \frac{\delta}{\eta} \frac{(\hat{\pi}_2/2)^{1/2}}{(v - r_2)^{1/2} - (\hat{\pi}_2/2)^{1/2}} \end{aligned}$$

Eliminating $p^*(r_1, r_2)$, the first two equations above yield

$$2\hat{\pi}_1(v - r_2) = (v - r_1)^2 + (\hat{\pi}_1 - v + r_0)(v - r_1) + \hat{\pi}_1(v - r_0)$$

while the last two equations indicate that

$$2\hat{\pi}_1(v - r_2) = \frac{\hat{\pi}_2}{\hat{\pi}_1}(v - r_1)^2$$

Note that the above two equations hold for all pairs of (r_1, r_2) that satisfy *Return Equivalence* and *On-Path*. However, obviously, at most two pairs of (r_1, r_2) could satisfy them simultaneously, as both terms $\hat{\pi}_1 - v + r_0$ and $\hat{\pi}_1$ are non-zero in equilibrium. Equate them and eliminate of r_2, and we have

$$\frac{\hat{\pi}_2}{\hat{\pi}_1}(v - r_1)^2 = (v - r_1)^2 + (\hat{\pi}_1 - v + r_0)(v - r_1) + \hat{\pi}_1(v - r_0)$$

Because $\hat{\pi}_2 \geq \hat{\pi}_1$, the above quadratic equation has only one positive root. Therefore, the pair (r_1, r_2) is uniquely determined. $\square$

Proof of Proposition 7

Case 1. To show that case 1 is satisfies the equilibrium conditions, we need to show that neither type has an incentive to deviate. First consider a size-two borrower who deviates by choosing interest rate $r_2 < \underline{r}_2$. In this case, his profit can be represented as

$$\tilde{\pi}_2(r_2) = 2\tilde{q}_2(r_2)^2(v - r_2)$$

Because there is no gap in investors' utility, there exists r_1 such that $q_1(r_1) = \tilde{q}_2(r_2)$. Therefore, the profit can be represented as

$$\tilde{\pi}_2(r_2) = 2q_1(r_1)^2(v - r_2)$$

By Equation (15a), we have

$$\frac{2q_1(r_1)}{1 + q_1(r_1)}(v - r_2) = v - r_1 + \frac{1 - q_1(r_1)}{1 + q_1(r_1)}(v - r_0)$$

Multiply both sides by $(1 + q_1(r_1))q_1(r_1)$; we have

$$\tilde{\pi}_2(r_2) = (1 + q_1(r_1))\hat{\pi}_1 - (1 - q_1(r_1))q_1(r_1)(v - r_0)$$

Hence, deviating to a rate $r_2 \in [r_0, \underline{r}_2]$ is equivalent to selecting a $q \in [q_1(r_0), q_1(\bar{r}_1)]$, i.e.,

$$\tilde{\pi}_2(q) = (1 + q)\hat{\pi}_1 - (1 - q)q(v - r_0)$$

Take the derivative w.r.t. q; we have

$$\frac{\partial \tilde{\pi}_2(q)}{\partial q} = \hat{\pi}_1 - (v - r_0) + 2q(v - r_0)$$

Because $\hat{\pi}_1 = q_0(v - r_0)$, verifying the sign of above derivative is equivalent to checking that of $q_0 - 1 + 2q$. As $\hat{\pi}_2 > \hat{\pi}_1$, it is easy to show that $q^* \equiv q_1(\bar{r}_1) > 1/2$ (A direct result from Lemma 7). Therefore, there exists $\tilde{q} \geq q_0$ such that $q_0 - 1 + 2q > 0$ for all $q \in [\tilde{q}, q^*]$. If $\tilde{q} = q_0$, then $\tilde{\pi}_2(q)$ will be increasing on the whole support. Otherwise, within $q \in [q_0, \tilde{q}]$, the term is decreasing. That is, within $q \in [\tilde{q}, q^*]$, $\tilde{\pi}_2(q)$ is increasing. Then, it is sufficient to show that $\tilde{\pi}_2(q_0) \leq \hat{\pi}_2$. Assume that $\tilde{\pi}_2(q_0) > \hat{\pi}_2$, then $2q_0^2(v - r_0) > 2q^{*2}(v - \underline{r}_2) > \hat{\pi}_1 = q_0(v - r_0)$, which indicates that $q_0 > 1/2$, so $q_0 - 1 + 2q$ is greater than zero for all $q \in [q_0, q^*]$, contradiction. Therefore, there is no profitable deviation for a size-2 borrower.

Next, consider a size-1 borrower's incentive to deviate by choosing $r > \bar{r}_1$. Again, by *Return Equivalence*, we have

$$\tilde{\pi}_1(r_1) = \frac{\hat{\pi}_2}{1+q_2(r_2)} + \frac{1-q_2(r_2)}{1+q_2(r_2)} q_2(r_2)(v - r_0)$$

Similarly, the problem is equivalent to deviating to $q \in [q_2(\underline{r}_2), q_2(\bar{r}_2)]$,

$$\tilde{\pi}_1(q) = \frac{\hat{\pi}_2}{1+q} + \frac{(1-q)q}{1+q}(v - r_0)$$

Again, taking derivative w.r.t. q, we have

$$\frac{\partial \tilde{\pi}_1(q)}{\partial q} = -\frac{\hat{\pi}_2}{(1+q)^2} - \frac{q^2+2q-1}{(1+q)^2}(v - r_0) < -\frac{\hat{\pi}_1}{(1+q)^2} - \frac{q^2+2q-1}{(1+q)^2}(v - r_0)$$

The inequality is guaranteed by $\hat{\pi}_2 > \hat{\pi}_1$. Further, the sign of the last term is equivalent to

$$-q_0 - q^2 - 2q + 1$$

As $q > q^* > 1/2$, the above term is negative. Therefore, $\frac{\partial \tilde{\pi}_1(q)}{\partial q} < 0$, which is a sufficient condition for there to be no profitable deviation for investors with size 1.

Case 2. Let us consider the case in which smaller projects have higher average rates. Specifically, $r_2 \in [r_0, \bar{r}_2]$ and $r_1 \in [\underline{r}_1, \bar{r}_1]$. As a size-2 borrower has no incentive to deviate to size 1, we have

$$2q_0^2(v - r_0) \geq q_0(v - r_0)$$

which indicates that $q_0 > 1/2$. Now, consider a size-2 borrower who deviates as above; then, we have

$$\tilde{\pi}_2(q) = (1+q)\hat{\pi}_1 - (1-q)q(v - r_0)$$

The derivative w.r.t. q takes the form $q_0 - 1 + 2q$, which is strictly positive because $q > q_0 > 1/2$.

□

Appendix C. Tables and Figures

Tables

Variable	Mean	Std. dev.	Min	Max
All Listings				
Loan Size	37,489.39	199,656	400	20,000,000
Interest Rates	0.126417	0.0334	10%	20%
Durations	29.31826	40.41698	1	810
Progress	49.07%	0.4448	0	100%
Number of Observations	508,888			
Primary Loans				
Loan Size	3,770,128	2,442,229	1,000,000	20,000,000
Interest Rates	18%	0	18%	18%
Durations	612.787	227.4511	180	810
Progress	100%	0	100%	100%
Number of Observations	939			
Secondary Loans				
Loan Size	30,442.37	48,530.61	400	5,000,000
Interest Rates	12.81%	0.0296	10%	20%
Durations	27.98	30.59	1	360
Progress	47.58%	0.4451	0	100%
Number of Observations	464,718			

Table 1: Summary Statistics of All Listings

Note: The data for this table summarize information on 508,888 listings. Moreover, I report the summary statistics for Primary Loans and Secondary Loans. The time horizon of the data is from January 2015 to May 2015. All interest rates are annualized; loan sizes are measured by CNY(1 USD = 6.2 CNY); duration is measured by day.

Variable	Mean	Std. dev.	Min	Max
1-Month Secondary Loans				
Loan Size	310,90.98	50,245.85	400	4,370,000
Interest Rates	14.32%	.0076	10%	20%
Number of Bidders	6.36	6.46	0	342
Progress	51.79%	.4270	0	100%
Number of Observations	297,685			
Number of Successful Loans	126,121			

Table 2: Summary Statistics of 1-month Secondary Loans

Rate	Listings	Funded Listings	Funding Probability	Funding Probability (Weighted by Size)
≥10%	789	65	8.24%	4.77%
≥11%	1,216	67	5.51%	8.84%
≥12%	7,508	1,582	21.07%	43.69%
≥13%	29,774	9,579	32.17%	47.27%
≥14%	204,445	88,942	43.50%	59.56%
≥15%	47,556	21,958	46.17%	54.54%
≥16%	6,397	3,928	61.40%	65.24%
Total	297,685	126,121	42.37%	57.34%

Table 3: Funding Probability by Interest Rate

Percentile	Funding Probability	Funding Probability (Weighted by Size)
10	7.75%	10.89%
20	32.87%	30.87%
30	36.81%	28.84%
40	40.88%	32.81%
50	49.95%	44.68%
60	50.99%	43.68%
70	62.79%	61.44%
80	66.95%	67.62%
90	75.42%	78.92%
Total	42.37%	57.34%

Table 4: Funding Probability by Rate

Note: The funding probability by percentile is computed by the average of hourly statistics.

	Daily	Weekly	Overall
Individual	0.3390%	0.5692%	0.5889%
Aggregate	0.4042%	0.4870%	0.6756%

Table 5: Individual-level Rate Dispersion

	Aggregate		Individual	
	10 Percentile	90 Percentile	Min	Max
Daily	13.78%	14.67%	13.93%	14.66%
Weekly	13.71%	14.84%	13.65%	14.89%
Overall	13.71%	15.21%	12.44%	15.88%

Table 6: Individual Rate Dispersion (min/max)

Rate Dispersion	Hourly	Daily	Weekly	Overall
All Listings	0.3403%	0.4042%	0.4870%	0.6756%
Successful Listings	0.1268%	0.2186%	0.3498%	0.6218%

Table 7: Rate Dispersion over Time

	Whole Sample	Group 1	Group 2
	DT_{it}	DT_{it}	DT_{it}
$PROGRESS\ CUMULATED_{it-1}$	-373.1***	1.260	-4045.1***
	(-52.25)	(1.57)	(-50.82)
$WEBSITE\ PAGE_{it}$	-6.316***	29.18***	60.47***
	(-9.36)	(297.67)	(14.99)
$LISTING\ AGE_{it}$	16.80***	1.209***	17.63***
	(555.25)	(99.88)	(154.25)
$SIZE_i$	-0.000910***	-0.000189***	-0.00712***
	(-31.33)	(-53.41)	(-25.58)
$RATE_i$	-8898.7***	-3280.3***	-90183.8***
	(-21.32)	(-69.09)	(-21.20)
L_t	0.0000118***	-0.00000602***	0.0000446*
	(6.40)	(-29.46)	(2.09)
I_t	-0.00000405	-0.00000697***	-0.0000685
	(-1.38)	(-21.40)	(-1.92)
V_{primary}	-0.000000904***	1.15e-08	-0.00000668***
	(-9.78)	(1.12)	(-6.69)
T_{primary}	-0.150***	0.0106***	-1.602***
	(-11.93)	(7.54)	(-11.80)
Daytime	28.71***	5.271***	133.4*
	(5.90)	(9.74)	(2.39)
Weekend	0.446	4.120***	366.3***
	(0.09)	(7.24)	(7.01)
Night	-22.08**	33.53***	171.6*
	(-2.83)	(37.45)	(2.39)
cons	1620.1***	516.7***	15753.1***
	(25.70)	(72.29)	(24.57)
Biddings	900,405	815,518	84,842
Listings	126,149	113,349	12,800
R-sq	0.3235	0.1742	0.3300

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Effect of Funding Progress

Note: The funding speed is computed only for fully funded listings. $WEBSITE\ PAGE_{it}$ is listing i's default page number at the time t; $LISTING\ AGE_{it}$ is listing i's age at time t measured in minutes; $SIZE_i$ and $Rate_i$ are listing i's size measured in CNY and annualized interest rate, respectively. L_t represents the amount of listing inflow at time t measure in CNY; I_t represents total amount of funding inflow at time t. Other control variables include V_{primary} and T_{primary} measures, which measure the total volume of primary loans and their respective duration measured by day; daytime represents the dummy if the time is between 9am and 5pm; night is the dummy if t is between 1am and 9am; weekday is the dummy if the time is from Monday to Friday. In the rest of the tables, the variables will be identically defined unless stipulated otherwise.

	Hourly	Daily
	r_t	r_t
V_t	1.42e-09***	2.33e-10***
	(16.29)	(9.66)
I_t	-7.09e-10***	-2.75e-10***
	(-4.98)	(-6.47)
V_{primary}	-3.20e-11***	-4.89e-11***
	(-9.55)	(-4.27)
T_{primary}	-0.00000470***	-0.00000168
	(-8.87)	(-0.98)
Daytime	0.00175***	
	(8.48)	
Night	0.00465***	
	(18.83)	
Weekday	-0.0000769	0.0000696
	(-1.82)	(0.52)
cons	0.144***	0.143***
	(323.70)	(104.66)
N	2234	94
R-sq	0.2851	0.6685

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Average Interest Rate and Market Supply/Demand

Note: r_t is the average rate at time t. In the first panel, t is measured in hours. In the second panel, t is measured in days.

	Hourly	Daily
	d_t	d_t
z_t	0.000261**	-0.0154
	(3.28)	(-1.05)
z_t^2	-0.00000265**	0.00650
	(-2.82)	(1.45)
r_t	0.508***	0.476***
	(24.63)	(6.28)
V_{primary}	1.06e-11**	1.66e-11
	(3.05)	(1.80)
T_{primary}	-0.00000376***	-0.00000110
	(-6.32)	(-0.70)
Daytime	-0.000831***	
	(-3.74)	
Night	-0.000744***	
	(-3.34)	
Weekday	-0.0000497	-0.000145
	(-1.07)	(-1.18)
cons	-0.0638***	-0.0512***
	(-20.49)	(-3.78)
N	2231	94
R-sq	0.2709	0.6454

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Rate Dispersion and Market Supply/Demand

Note: d_t is the rate dispersion measured by JNS statistics. In the first panel, t is measured in hours. In the second panel, t is measured in days.

	Hourly	Daily
	r_{it}	r_{it}
$Size_{it}$	1.64e-08***	1.70e-08***
	(77.77)	(75.35)
L_t	0.0000620***	0.00000821***
	(8.38)	(3.99)
V_t	5.99e-08***	1.40e-08***
	(13.23)	(8.61)
I_t	-6.05e-08***	-1.42e-08***
	(-13.25)	(-8.65)
$V_{primary}$	-2.40e-11***	-2.41e-11
	(-6.69)	(-1.81)
$T_{primary}$	-0.00000709***	-0.00000288
	(-12.30)	(-1.51)
Weekday	-0.0000594	0.0000962
	(-1.31)	(0.64)
Daytime	0.00128***	
	(5.99)	
Night	0.00466***	
	(16.65)	
cons	0.145***	0.139***
	(288.60)	(81.55)
N	106237	106237
R-sq	0.1505	0.1301

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: Correlation between Sizes and Rates

	Daily	Hourly
	N_t	N_t
L_t	-4.402***	-80.73***
	(-814.56)	(-427.79)
I_t	0.000266***	0.00468***
	(551.48)	(360.14)
$V_{primary}$	0.0000295***	0.0000341***
	(113.59)	(64.13)
$V_{primary}$	0.847***	1.551***
	(20.40)	(17.39)
Night		-2757.5***
		(-58.77)
Daytime		-3147.5***
		(-106.39)
Weekday	-413.9***	-407.7***
	(-123.44)	(-54.65)
cons	29308.5***	30883.6***
	(840.52)	(410.81)
N	116	2696
R-sq	0.8031	0.5316

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: Average Loan Size

Note: N_t measures average number of investors for each successful listings. In the first panel, t is measured in days. In the second panel, t is measured in hours.

	Mean	SD	95% C.I.
0	0.3580	0.0828	[0.1923, 0.5236]
10%	0.4674	0.1020	[0.2633, 0.6715]
20%	0.6311	0.1615	[0.3080, 0.9542]
30%	0.7286	0.1971	[0.3343, 1.1229]
40%	0.8333	0.2144	[0.4045, 1.2622]
50%	0.9772	0.2420	[0.4932, 1.4612]
60%	1.2539	0.3183	[0.6172, 1.8906]
70%	1.2995	0.2788	[0.7417, 1.8572]
80%	1.2999	0.2636	[0.7725, 1.8272]
90%	1.6737	0.3112	[1.0513, 2.2962]
100%	1.7649	0.2851	[1.1946, 2.3351]

Table 13: Estimate of $H(x)$ with 10th Percentile

Mean	SD	95% C.I.
0.3844	0.0860	[0.2124, 0.5565]
0.6152	0.1629	[0.2893, 0.9410]
1.0356	0.3664	[0.3027, 1.7684]
1.4727	0.5697	[0.3332, 2.6122]
1.8020	0.5495	[0.7031, 2.9010]

Table 14: Estimate of $H(x)$ with 25th Percentile

Figures

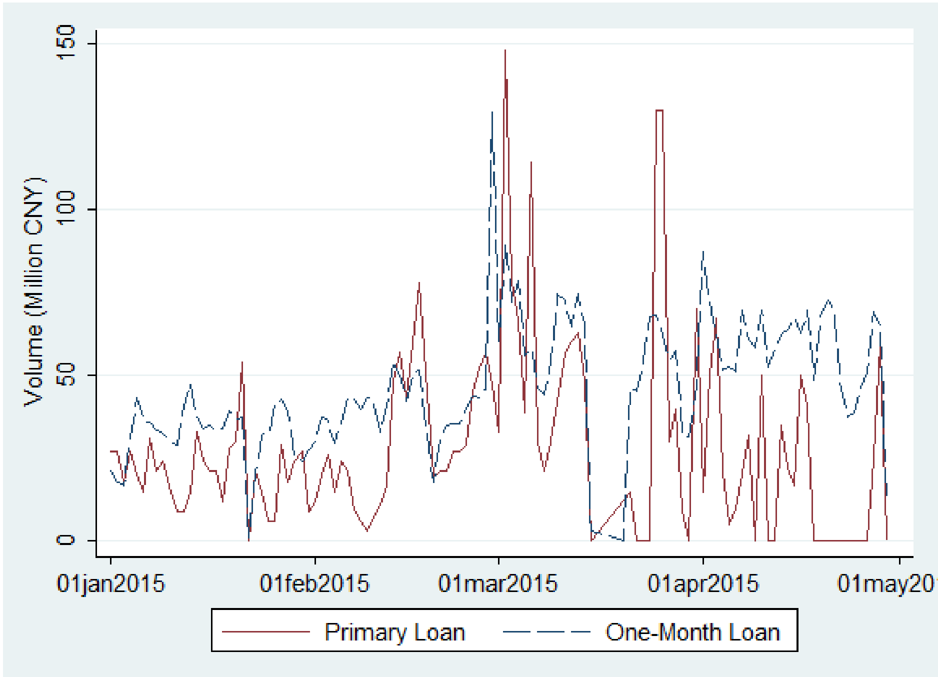

Figure 1: Volume of Different Types of Loans

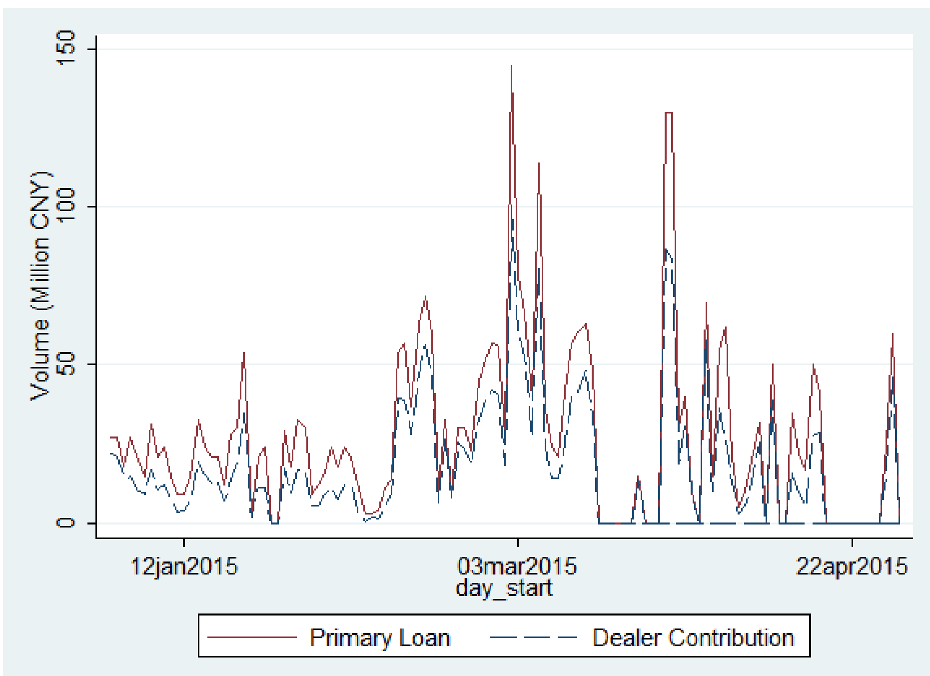

Figure 2: Volume of Different Types of Loans

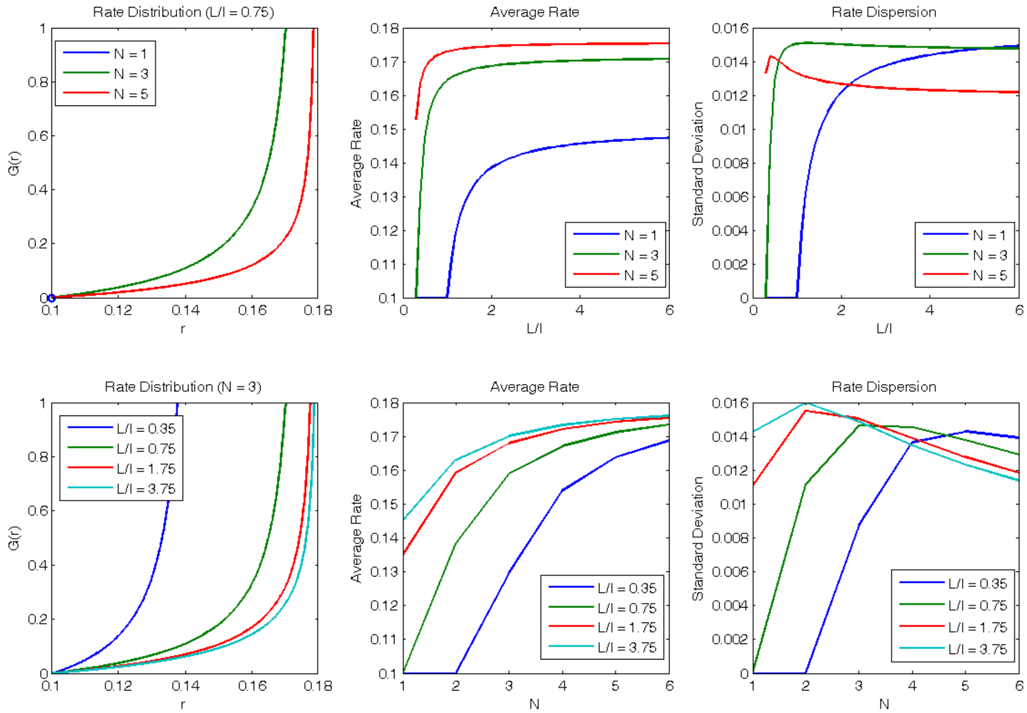

Figure 3: Rate Distribution vs Supply and Demand

Note: First row reports the change of rate distribution, average rate and rate dispersion w.r.t. different loan size N; Second row reports the change of rate distribution, average rate and rate dispersion w.r.t. different supply demand ratio L/I; For parameters, let $\delta = 0.9, r_0 = 0.1, v = 0.18$. For the distribution of ℓ, I apply distribution used in (Burdett and Menzio, 2013), letting $\Pr(\ell = 1) = 1 - \lambda; \Pr(\ell = 2) = \lambda$ and choose $\lambda = 0.7$. As shown in Figure 5, it is closed to my estimated result.

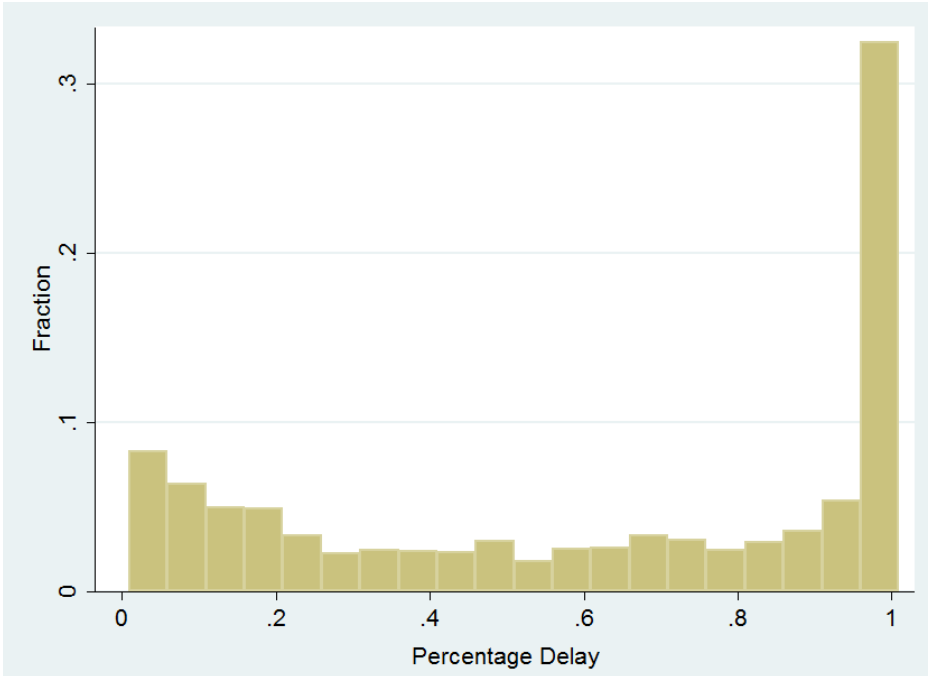

Figure 4: Distribution of Progress Delay

Note: We measured real progresses by cumulatively adding investors' bidding amount prior to the time they bid. The delay is measured by the real progress minus the progress shown on website snapshots at the same time.

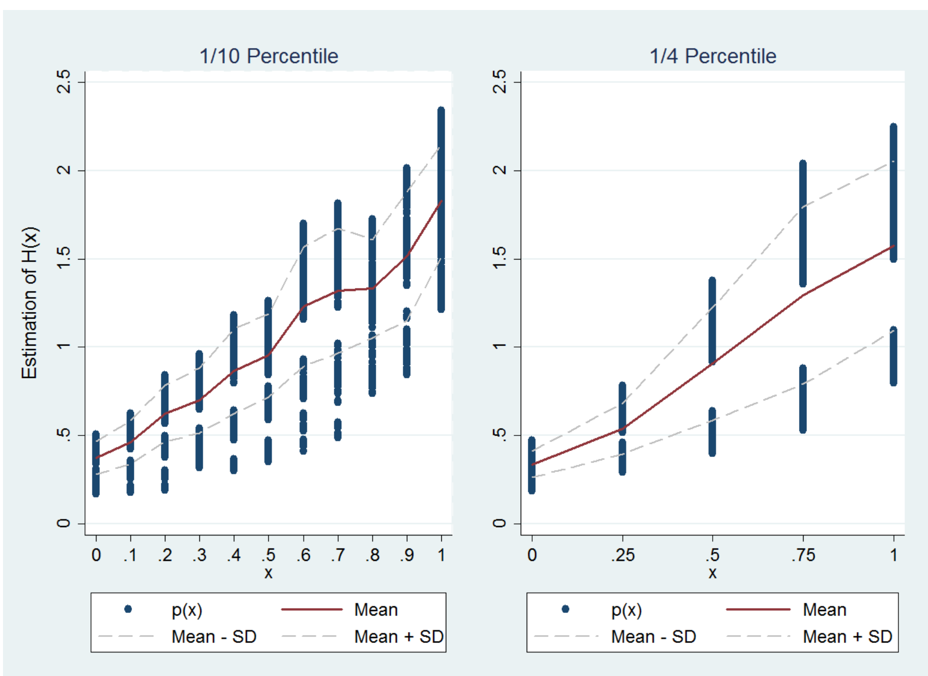

Figure 5: Estimates of $H(x)$

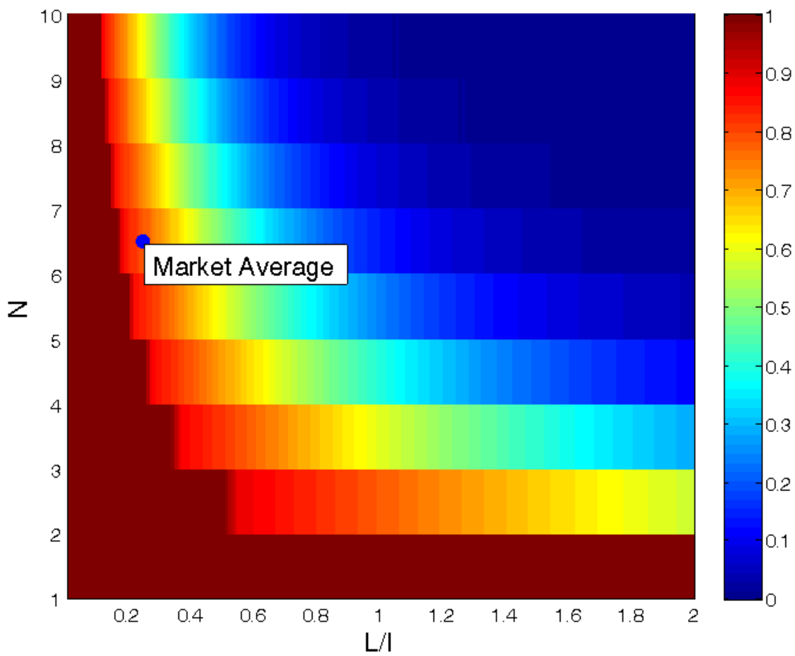

Figure 6: Calibrated $\frac{\mathcal{W}_{\text{random match}}}{\mathcal{W}_{\text{dispersed price}}}$