Survival Scale: Marketplace Lending and Asymmetric Network Effects*

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Abstract

We utilize a large panel data of peer-to-peer (P2P) lending platforms in China to examine the determinants of platform dynamics in an emerging industry characterized by entries, exits, and network externalities. We find that cross-side network effects (CNEs) captured by standard elasticity measures alter platforms' scale, which in turn affect future platform performances through customer matching and risk diversification. CNEs are persistent and lenders' CNEs are asymmetrically larger during platform growth than during platform declines. Borrowers' CNEs are symmetric and indicate borrowers' greater stickiness. Lenders' CNEs also dominate borrowers' in foretelling failures and, together with scale, strongly predict platforms' long-term likelihood of survival since inception. These asymmetric network effects reflect distinguishing features of financial platforms, inherent differences between lenders and borrowers, and contracting or agency frictions. Overall, our empirical findings and their novel economic channels inform practitioners, investors, and regulators, while providing insights about industry-wide dynamics of multi-sided platforms.

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1. Introduction

Two-sided markets are prevalent in a vast array of industries covering credit cards, Internet-based IT firms, video games, portals and media, payments, etc. They play increasingly important roles in the global economy with the rise of giant platforms such as Alibaba, Amazon, and Facebook. While the economics of two-sided platforms has emerged over the past decades as one of the most actively researched areas in business economics, studies typically focus on pricing and rely on one or two growing platforms, leaving out systematic patterns about network externalities in the cross-section of the industry and dynamics of struggling or failing platforms.[1] Little distinction has been made between emergent financial platforms and traditional marketplaces either.

At the same time, marketplace lending, also known as P2P lending, has experienced phenomenal growth. Its largest market is China, with more than 6,000 P2P platforms having been introduced over the past decade according to the 2018 P2P online lending yearbook (www.wdzj.com). In 2018 alone, 19 million investors and 13 million borrowers in China participated in P2P lending and the transaction volume amounted to US $178.89 billion, as compared to US $8.21 billion in the United (States Statistia Research, 2019). Moreover, more than two thirds of the platforms in China have failed or were under serious stress by the end of 2018. For the first time, FinTech platforms constitute a significant fraction of the economy and their massive failures indisputably raise concerns about financial stability and systemic risks.

Why do some lending platforms fail while others survive? What roles do platform scale and network effects play when platforms grow and decline? What distinguishes these financial platforms from other platforms, especially when it comes to the risks various parties face? Despite recent studies on lending marketplaces and frequent media discussions of fraudulent activities and macroeconomic conditions, we understand little about the cross-section and evolution of two-sided platforms, especially those in the P2P lending industry.

[1]The 2014 Nobel Prize in Economic Sciences was awarded to Jean Tirole in part due to his work on multi-sided platforms that started a literature beyond that of multi-product pricing.

To this end, we utilize a novel data set of about 1,000 of Chinese P2P lending platforms to examine the factors influencing their performance, failure, and competition in an emerging market. We find that cross-side network effects (CNEs) as captured by simple elasticity measures significantly affect platforms' future performances. They alter the scale of platform activities which in turn predict to platform failures.[2] We also provide evidence that the unique features of financial platforms and inherent differences between lenders and borrowers' objectives lead to asymmetric CNEs, with lenders' CNEs being significantly larger for growing platforms than for declining platforms and jointly with platform scale predominantly driving platforms' dynamics.

Marketplace lending in China is well-suited for studying two-sided financial platforms. Evidently, FinTech has the biggest impact in emerging economies where traditional financial sectors fail to meet rising demands; internet-based marketplace lending takes advantage of wide geographical coverage and fast processing speed, and utilizes big data and advanced algorithms to effectively serve the unbanked as well as small and medium enterprises. Yet emerging markets also tend to lag behind in terms of legal and financial systems, which leads to significant market frictions that are often negligible in developed countries. Such frictions coupled with unique features of financial platforms lead to these novel empirical observations that can inform theory and practice. Importantly, observing the large panel of platforms, both growing and failing, allows us to study network effects systematically for the first time rather than relying on one or two thriving platforms with idiosyncratic characteristics.

We first show that platform scale, proxied by trading volume, has strong predictive power on platform failure because a larger scale corresponds to a better matching efficiency and a greater diversification of credit risks. A 10% growth in scale reduces the odd of failure by as much as 3% in a month. In the cross-section, one standard deviation increase of log platform scale decreases the failure probability over the next year by 20%, by reducing the average origination time fivefold and the investment and

[2] A platform fails when there is no more transaction. We do not observe and are therefore agnostic on whether the failure is driven by all users leaving or by the owner's closure of the platform. In Appendix A(g), we discuss the various failure mechanisms based on manually investigations of a random sample in our data.

loan concentrations by 17.4% and 17.7% respectively at a monthly basis.

We then show that platform scales are in turn driven by CNEs---the elasticity of the number of new trades by agents on one side to the active number of agents from the other side of P2P platforms.[3] While the extant literature mainly uses historical time-series data of individual platforms, our paper is among the first to construct time-series indices for a large cross section of platforms to analyze idiosyncratic CNEs using panel data. The large number of P2P lending platforms in China enables us to compare platforms with different characteristics and analyze the role of network effects on industry evolution.

With the elasticity measure of CNE, we find that both lenders' and borrowers' CNEs are significant and persistent, i.e., increases in lenders' participation lead to subsequent increases in borrows' participation and vice versa. Moreover, failed platforms have CNEs far below the healthy platforms. Further panel analyses reveal the first asymmetry: lenders' CNEs is about three times smaller when the number of lenders decreases than when it increases. In contrast, there is no such asymmetry for the borrowers' CNEs. As a result, a second asymmetry arises wherein the lenders' CNE dominates borrowers' in determining a platform's survival. A one standard deviation increase in lenders' CNEs forecasts a 1.12% increase in platform scale and a 0.43% decrease in failure probability over the next month.

We then argue that the interaction between CNEs and financial frictions on P2P lending platforms likely contribute to the aforementioned empirical observations. First, reckon that financial platforms typically involve long-term contracts (e.g., loans) and are not transactional (unlike other platforms such as Amazon). Investors thus need to diversify across projects residing on different platforms. Even if borrowers all multihome (adopt multiple platforms) and platforms take actions to mitigate the risk of borrowers' defaulting (e.g., by offering principal guarantees), lenders still face the risk

[3] There are two types of network effects: same-side (direct) and cross-side (indirect) network effects. The same-side network effect measures the incremental benefit for an existing user as each new user on the same side comes into the network. The cross-side network effect measures the incremental benefit for an existing user on one side of a platform when each new user on the other side of the platform joins the platform.

of platform failure or a run among investors on the platform. Therefore, investors would either rotate across various platforms or multihome in order to diversify such risk.

In stark contrast, borrowers face no risk-diversification issues and find it costly to list on multiple platforms. Projects are also often “one shot” short-term projects and entrepreneurs choose platforms that best suit their project. Once a campaign ends, they may choose a different platform for another project, but they have to apply and get approved, which is an elaborate and costly process (e.g., see Appendix A Figure A1), comparing to the little effort or cost investors incur to join a platform. Consequently, the two sides have vastly different objectives and risks. Because the lenders have greater needs for diversification, face smaller costs of adopting new platforms, and do not rely on reputation building, they are easier to attract once borrowers join the platform.

Why lenders’ CNE matters less when a platform is shrinking (the first asymmetry)? It turns out that borrowers respond less when lenders are leaving. First, borrowers are on the receiving side and are less concerned with platform failures because they benefit if the platform no longer pursues them for paybacks. Second, borrowers still have to provide much information in addition to exerting effort when applying to other platforms. To the extent that privacy is valuable and effort is not free, switching is costly. Finally, borrowers typically build a reputation or stimulate social interactions on a particular platform (Burtch et al., 2014). Without a well-established credit rating or reference system in China, many credit systems for borrowers are proprietary, making it hard for borrowers to multi-home or switch easily. Informational frictions about a borrower’s type thus imply that borrowers are less willing to depart from the declining platform --- they are more sticky than lenders on P2P platforms.

Lenders’ CNEs are thus more important because it is crucial to acquire borrowers; if a platform can attract more borrowers with the same increases in lenders, it tends to grow faster (the second asymmetry). We further show that lenders’ CNEs jointly with platform scale can serve as a robust early predictor of future platform failure rate and lifespan. One standard deviation increase in the first-year lenders’ CNE decreases the probability of platform failure by 7.3% whereas that in platform scale, by 12.9%.

We conduct a number of robustness tests and further analyze the empirical observations. Interestingly, state ownership is a predominant driver for the borrowers' CNE but not the lenders' CNE during the takeoff period. In contrast, population in the platform's home city explains both CNEs. None of the intrinsic platform characteristics explain CNEs when platforms are declining and falling.

Our findings about platform scale and asymmetric CNEs have implications for platform owners, investors, and regulatory authorities. Platform owners, for example, should aim for effective translation of lender acquisition to borrower growth, especially on nascent platforms. Investors can use platform characteristics to better screen platforms to adopt. Regulators can potentially disclose information about, for example, platform scale and CNEs, in order to guide retail investors to better manage risks associated with platform failures.

Our paper foremost relates to studies on network externalities and competition in two-sided markets. Since the seminal work of Rochet and Tirole (2003) highlighting the prevalence of two-sided markets and the importance of price allocation, subsequent studies have derived price dependence on the size of the network externalities and agents' multihoming (Armstrong, 2006) as well as price structure to "get both sides on board" (e.g., Rochet and Tirole 2006). Beyond pricing, Clements and Ohashi (2005) show that CNEs and positive feedback loops exacerbate platform competition. Moreover, Lee (2013) models the video game industry and empirically finds that higher platform compatibility increases the sales of software and hardware and improves consumer welfare. We contribute by uncovering asymmetries in network effect and relate them for the first time to unique features of financial platforms.

CNEs naturally entail the "chicken-and-egg" paradox, i.e., lenders might wait to join a platform until enough borrowers have applied for loans; yet borrowers may decide to list their loans on a platform until a large number of active lenders exist in a platform (Caillaud and Jullien 2003; Gupta et al 1999). Katz and Shapiro (1994) argue that the growth of software availability tends to concur with hardware sales, while Stremersch et al., (2007) document that hardware sales precede software availability but not vice versa. We find that CNEs for both the lenders and the borrowers are present, with the lenders' CNE playing a more important role on the survival of P2P platforms.

Empirically, a large literature measure CNEs in VCRs (Ohashi, 2003), video games (Shankar and Bayus, 2003), personal digital assistants and software (Nair et al. 2004), etc.[4] Our measurement follows closely the recent approach in the literature: Chu et al (2016) compute the CNE as the increase in the number of new buyers (sellers) when sellers' (buyers') installed base increases by 1%. To measure software and hardware CNEs, Stremersch et al. (2007) use the elasticity of hardware sales to lagged software availability and that of software availability to the lagged hardware installed base. To our best knowledge, we are the first to apply such measures to financial platforms which differ from other platforms in many aspects. We are also among the first to study the performance and dynamics of platforms using a large panel dataset. In particular, our analysis for declining platforms fills in the gap in the empirical literature in that prior studies focus on CNEs only for platforms are growing and thriving whereas we examine CNEs both when platforms are booming and when they are in distress (failing).

This paper adds equally to the emerging literature on marketplace lending, which has largely centered around competition and complementarity between platforms and banks as well as the quality of screening. Lin, Prabhala, and Viswanathan (2013) use data from Prosper.com and find online friendships of borrowers act as signals of credit quality; along the same vein, Jagtiani and Lemieux (2017) show how alternative data enable LendingClub to outperform traditional lending; Roure, Pelizzon, and Thakor (2018) find that P2P lenders bottom fish when regulatory shocks disadvantage banks; Vallee and Zeng (2019) analyze the optimal information distribution for marketplace lending; Tang (2019a) finds that P2P lending is a substitute for bank lending in terms of serving infra-marginal bank borrowers yet complements bank lending with respect to small loans; finally, Allen, Peng, and Shan (2019) shows that on LendingClub approval rates and quality are higher for regions with greater aggregate online social connections. None of the studies examines multiple lending platforms and their

[4] It is also related to practitioners' heuristic concept of platform stickiness---the ability to retain users or to extend the duration of their usage on the platform, one of the key variables for the success of e-commerce platforms (e.g., Caruana and Ewing, 2010 and Rafiq, Fulford, and Lu, 2013).

industrial organization. Most also use data from the United States and Europe, leaving out the largest market for P2P lending. The rare exception is Jiang, Liao, Wang, and Zhang (2018) which studies whether government affiliation is a valid signal about platform quality in China. We focus on asymmetric CNEs and the mechanisms extend beyond P2P lending and the Chinese crowdfunding market. We also analyze how various platform attributes affect network effects and platform scale.

More broadly, our paper relates to FinTech and crowdfunding (both reward-based and equity-based) platforms.[5] Also studying network effects in crowdfunding is Bellefamme, Lambert, and Schwienbacher (2019) that uses data from two competing reward-based crowdfunding platforms in France to analyze the interplay of social learning, network effects, and platforms' performance. The authors focus on same-side network effects on reward-based platforms, which complements our study on CNEs on P2P lending platforms. The cross-project learning channel they identify also helps microfound our economic channels. We add by identifying unique features and frictions concerning financial platforms and provide evidence of their impact on the industry evolution. The Chinese context highlights the role of technology for financial development and inclusion in emerging economies as well.

The remainder of the paper is organized as follows. Section 2 describes our data. Section 3 presents the empirical link between platform scale and failure rates. Section 4 measures CNEs empirically and analyzes their impact on platform scale and evolution. Section 5 further interprets asymmetric CNEs and discusses their implications for practitioners, investors, and regulators. Section 6 concludes.

2. Data Description

We mainly utilize two datasets, both from Zero One Finance, a private data vendor specializing in P2P lending data. The first dataset covers transactions on 1,404 P2P

[5] For example, Franks, Serrano-Velarde, and Sussman (2016) examine the tension between information aggregation of auctions on Funding Circle and their susceptibility to liquidity shortages; Wei and Lin (2016) study market mechanisms on online P2P platforms; Buchak et al. (2018) examine regulatory arbitrage and online mortgage lenders; Cong and Xiao (2019) study information aggregation and pricing efficiency when platforms implement all-or-nothing thresholds.

platforms at a weekly frequency from June 26, 2007, to June 30, 2018.[6] We first delete platforms deemed fraudulent by Chinese courts, because our paper focuses on general economic mechanisms, not frauds or Ponzi schemes. We then remove platforms with a lifespan of less than one year because our measure of CNEs requires at least one year of observation. Overall, our data contain transactions on 988 platforms with 141,322 weekly observations. The platforms in our data are reasonably representative of the industry, covering 68% of the trading volume in the entire P2P market in the year 2017.[7]

Our dataset contains starting and closure dates of platforms and their transaction data. Panel A of Table 1 documents the distribution of the starting years of platforms: only 13 platforms existed before 2012, but since then new platforms kept increasing until 2016 when the People's Bank of China imposed strict regulations on P2P lending. Among the 988 platforms, 418 (42%) have failed and 570 (58%) are live as of June of 2018. The average life span of failed platforms is around 2.2 years and that of live platforms is about 3.5 years.

The transaction data include the following variables on each platform during each week: the number of investments, the number of loans, trading volume (in the unit of 10,000 RMB), the average interest rate, the average loan/investment size, average origination time (in seconds), average number of loans per borrower/lender, average investment size per lender and average loan size per borrower.

Panel B of Table 1 lists the average and standard deviation of all platforms and for live and failed platforms, respectively. The number of investments for live platforms is about four times $(\exp(5.777 - 4.455))$ that of failed platforms, while the number of loans for live platforms is about three times relative to that of failed ones. The trading volume of live platforms is about five times that of failed platforms. These facts inform that live platforms, on average, have a larger scale than failed ones. The loan and investment sizes are both larger (56% and 20% more) for live platforms than failed ones.

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[6] The earliest P2P lending platform in China is PaiPaiDai (http://www.ppdai.com/), which started in 2007. Since then, the number of P2P platforms started to increase rapidly, the years of 2014 and 2015 saw a strong increase in numbers of P2P platforms. From 2011 to 2018, there are more than 5,000 platforms existing in the market, but more than 50% of them failed by the end of the year 2018.

[7] Note that, our data covers 1.91 trillion yuan of trading volume, while the total trading volume of Chinese P2P market is 2.80 trillion yuan according to https://www.wdzj.com/news/yc/1730395.html.

The number of loans per borrower and the number of investments per lender are also larger (72% and 120% more, receptively) for live platforms relative to failed ones. Furthermore, borrowing amount per borrower is 60% more for live platforms relative to defunct ones, and the investment amount per lender is 40% more for live platforms than failed ones. The average interest rates for live and failed platforms are 11.7% and 16.1%, respectively. The origination time of a loan on ex-post live platforms is only 22.2% ($\exp(8.951 - 10.455)$) of that on ex-post failed ones. Overall, both borrowers and lenders are more active in live platforms than failed ones.

Our second dataset contains the measurement of concentration for both lenders and borrowers on a subset of platforms. The percentage of the top 10 largest investments or loans averaged along each month is reported at a monthly frequency. We have 745 platforms with investments concentration data and 402 platforms with loan concentration data. Panel B of Table 1 shows that the loan concentrations are 57.6% vs. 81.6%, and investment concentrations are 46.7% vs. 56.8%, for live and failed platforms respectively.

Finally, we also manually collect information on selected platforms from www.wdzj.com, the largest information aggregator of P2P lending in China, about the city of headquarter, its associated GDP and population, and whether the platform is owned or funded by a State-owned Enterprise (SOE).

3. Scale and Platform Failure

In this section, we first document how scale affects platforms' survival. We then explore possible mechanisms entailing matching efficiency and risk diversification. As shown in Figure 1, the survival rate (estimated from the Kaplan and Meier methodology) keeps going down, staying around 40% after 4 years. Taking the trading volume (in the unit of RMB 10,000) as a proxy for the scale of a platform, we draw the average scale of the platforms in their first year and their subsequent failure rates in Figure 2. In particular, we classify platforms in quartiles first, and calculate the failure rates after one, two, or three years for platforms within those quartiles. Clearly, there is a downward-sloping relationship between failure rates and the platform scale for all three measures of failure rates. A larger platform has less future failures.

Next, Table 2 displays the characteristics of platforms of different scale. Specifically, we first sort all platforms into large and small groups according to their scale. We then calculate the average of characteristics of the two groups and their differences. The number variables (including the number of investments, loans, borrowers and lenders) and size variables (including loan size, investment size, the amount per borrower, the amount per lender) for large platforms are all significantly greater than those of small platforms. There are more people on both sides of larger P2P platforms. People also tend to invest and borrow more on larger platforms. Furthermore, both the loan and investment concentration for large platforms are significantly smaller, which indicates a better diversification of loans and investment for large platforms. The interest rates in the large group are, on average, 3% less than those in the small group.

3.1 Empirical Links between Scale and Platform Failure

We next test a simple relationship between a platform's scale and its failure or survival by running a Fama-MacBeth regression. Specifically, at each time t, we run a cross-sectional regression across all platforms; we then report the mean and t-statistics of each coefficient in its time series throughout the sample period.[8]

We take interest rates, average loan size, and average lender' investment on a platform as control variables for the following reasons. Interest rates are normally considered as a proxy for risk of loans; they also reflect the cost of funds which may affect lenders' profitability and lending decisions. Loan sizes are normally determined by the needs of the projects (demand for funds), hence can be taken as exogenous in our tests. A lender's investment amount normally depends on the availability of his/her funds, for example, the personal wealth or willingness to invest on P2P platforms. Moreover, loan and investment sizes might also relate to the style of platforms. Take two well-known P2P platforms, Lujin Service and Hongling Venture Capital, for example. The daily

[8] We run a Fama-Macbeth regression to overcome the non-stationarity issue of platform scale, which clearly have trends as platforms grow.

loan amount of the former is only 28.7K yuan on average and has a maximum value of 316.2K yuan, while the daily loan amount of the latter is 730K yuan on average and has a maximum value of 40 million yuan. Moreover, these two variables can affect borrowers' decisions. For example, the average loan amount is indicative of the possibility of a successful loan application. If a borrower wants to get a large loan while a certain platform mainly engages in small loans, she is less likely to borrow successfully on the platform. A small investment amount also implies that the same target amount of loan requires more bidders to finish, which may lead to relatively longer origination time. Therefore, loan size and investment amount tend to have a significant effect on the decisions of players on both sides of a platform and hence its performance.

In order to compare the characteristics of various platforms at the same stage of their lifecycle, we line up platforms by their lifetime instead of calendar time and then include calendar dummies to control for the time fixed effects. Since platforms do not fail at a weekly horizon, in order to run the regression with the platform failure as the dependent variable, we use a Fama-MacBeth regression at monthly frequency:

$$F_{i,t+1} = b_0 + b_1 lnV_{i,t} + b_2 I_{i,t} + b_3 lnLS_{i,t} + b_4 lnIA_{i,t} + \sum_j^T k_j Y_j(i,t) + u_{i,t+1} \quad , \quad (1)$$

where $F_{i,t+1}$ is a dummy variable that is set to 1 when the ith platform failed at t+1th month and 0 otherwise; $lnV_{i,t}$ is the average log trading volume of the ith platform at month t, $I_{i,t}$ is the average interest rates at tth month across all projects on the ith platform, $LS_{i,t}$ is the average loan size across all borrowers on the ith platform at month t, $IA_{i,t}$ is the average investment amount across all lenders on the ith platform at month t. t is indexed by the lifetime of a platform at a monthly frequency, from the start of the second to the end of the fourth years (36 regressions). $Y_j(i,t)$ is a calendar year dummy, when the lifetime t of the ith platform is in the calendar year j, $Y_j(i,t)$ is set to 1 and otherwise 0. Specifically, j takes the following range: 2012 and before, 2013, 2014, 2015, 2016, 2017 and after. At each time t, we run a cross-sectional regression for all *live* platforms and then obtain a time series of coefficients. Understandably, the number of observations decrease as time goes on, in the last month, totally 142 observations left in the regression. The final coefficients are estimated by taking the mean of the time series with the standard deviations adjusted by the Newey-West method with 36 lags. We use both OLS and logit model to perform regressions, and results are reported in Table 3.

Both the uncontrolled and controlled OLS regressions produce estimations that are significant; roughly a 10% growth of a platform results in a 0.1% decrease in platform failure over the next month, about 1% in a year. From the logit regression, we see around a 3% decline in the odds in a month with 10% growth of scale. In the cross-section, one standard deviation increase (1.72) of log platform scale tends to decrease 1.7% monthly failure probability, which corresponds to a 20% drop on an annual basis. Overall, larger platforms tend to have smaller probabilities of failure.

In the next two subsections, we analyze two specific channels to understand the influence of platform scale on survival and failure rates.

3.2 Platform Scale and Matching Efficiency

P2P platforms connect lenders and borrowers, so larger platforms have more lenders and borrowers on both sides (also refer to Table 2). If these projects are heterogeneous, it is relatively easier for the lenders to find their favorite projects and therefore have a better matching efficiency. We take the origination time of achieving the full amount of a loan as a proxy for matching efficiency. We then expect a larger platform to have a shorter origination time on average. Table 2 shows that the large group of platforms only have, on average, a 24% origination time relative to that of the small group.

We run a Fama-MacBeth regression to estimate the relationship between platform scale and matching efficiency:

$$lnM_{i,t+1} = d_0 + d_1 lnV_{i,t} + d_2 I_{i,t} + d_3 lnLS_{i,t} + d_4 lnIA_{i,t} + \sum_j^T k_j Y_j(i,t) + u_{i,t+1}, \quad (2)$$

where $M_{i,t+1}$ is the origination time (in seconds) for the i^{th} platform at the $(t+1)^{th}$ month of its lifetime. Table 4 list the results, where we find higher matching efficiency in large platforms than in small ones. For example, with one standard deviation increase of (log) platform scale, the average origination time becomes 22% of the original.

3.3 Platform Scale and Risk Diversification

Diamond (1984) shows that large banks tend to have a portfolio with more loans and hence achieve a better risk diversification. For P2P platforms, a similar notion applies. The only difference is that P2P platforms have two sides, thus risk diversification on both sides is important for the health of the platform. For example, given a concentrated lenders' side, if one large investor leaves the platform, many loans are left unfunded. On the other hand, if loans are very concentrated, one default can lead to a large proportion of investors going uncompensated and therefore hurt the reputation of the platform.

In this paper, we use the percentage of top 10 investments and loans as the measure of concentration on the lenders' and borrowers' sides, respectively. A high concentration means a low level of diversification. Table 2 shows that the group of large platforms tends to have 24.8% and 24.4% less concentrated than the small-scale group for loan and investment concentration, respectively. To formally test the risk diversification and scale relationship, we run:

$$C_{i,t+1} = d_0 + d_1 lnV_{i,t} + d_2 I_{i,t} + d_3 lnLS_{i,t} + d_4 lnIA_{i,t} + \sum_j^T k_j Y_j(i,t) + u_{i,t+1}, \quad (5)$$

where $C_{i,t+1}$ is the percentage of top 10 investment and loans in the i^{th} platform at the $(t+1)^{th}$ month of its lifetime, respectively. Table 5 contains the results. Both investment and loan concentration decrease in platform scale, and hence platforms with larger scales achieve a better risk diversification. For example, one standard deviation increase of (log) platform scale leads to a drop of 17.4% and 17.7% for investment and loan concentration.

In sum, we find a platform's scale to be an important determinant of its future survival: A large platform is less likely to fail. We also identify two mechanisms for the relationship: matching efficiency and risk diversification. We next analyze CNEs, important determinants of platform scale.

4. Cross-side Network Effects and Platform Evolution

CNEs are a defining feature of two-sided markets and internet-based platforms. When a new user enters into a certain side of a P2P platform, users on the other side face more choices and hence higher chances of reaching a deal. Specifically, borrowers on a certain platform has a positive influence on the utility of the entire group of lenders, thereby attracting more lenders to invest in the platform and hence increasing the probability of loan origination. At the same time, lenders on a platform positively affect borrowers' decision to borrow. The more active lenders, the larger is the market potential for borrowers to achieve funding goals; more borrowers in turn attract more lenders to the platform. Therefore, boosting CNEs constitutes an integral task for platform owners.

a. Measurement of Network Effects

We follow Chu et al. (2016) and Stremersch et al. (2007) to measure the *elasticity* of increases in new loans initiated by borrowers in period t to the number of "active" lenders in period t-1, and then call that the lenders' CNE at time t. Similarly, we use the elasticity of increases in the number of new investments by the lenders in period t to the number of active borrowers in period t-1 as the borrowers' CNE at time t. We proxy "active" lenders (borrowers) in week t as cumulative numbers of lenders (borrowers) in the past four weeks (from t-3 to t): Because many of the loans are for credit card payments or personal debt consolidation, it is likely that borrowers raise funds at a monthly frequency.[9] Moreover, since most Chinese people receive salaries on a monthly basis, it is also likely that retail lenders invest at such frequencies.

There are several confounding issues empirically. The number of loans in the prior period may affect the number of newly issued loans for two reasons. First, a higher prior number of loans is likely to increase the payoff to lenders, which increases the future credit available to borrowers, generating a serial dependence. Second, prior loan availability yields more intense competition among borrowers, reducing the probability that borrowers can get funded and discouraging them from borrowing. This so-called "competition effect" yields a

[9] This can be found on the loan purpose of lending club (https://www.lendingclub.com).

negative serial relationship of borrower numbers. Overall, both phenomena concern same-side network effects. For the same token, the prior number of lenders may also increase or decrease the number of lenders in the next period.[10] Therefore, in measuring the CNEs we need to control serial dependence on the same side.

Similar as before, we use the lagged one period variables of interest rates, loan size and the investment amount per lender as control variables.[11] We run a weekly time-series regression to measure the CNEs for both the borrowers and lenders:

$$lnN_{i,t+1}^{Inv} = b_0 + b_1 lnCN_{i,t}^{Borrower} + b_2 lnN_{i,t}^{Inv} + b_3 I_{i,t} + b_4 lnLS_{i,t} + b_5 lnIA_{i,t} + u_{i,t+1} \quad (6)$$

$$lnN_{i,t+1}^{Loan} = c_0 + c_1 lnCN_{i,t}^{Lender} + c_2 lnN_{i,t}^{Loan} + c_3 I_{i,t} + c_4 lnLS_{i,t} + c_5 lnIA_{i,t} + u_{i,t+1}, \quad (7)$$

where $N_{i,t}^{Loan}$ is the total number of loans listed on a platform *i* at week *t*; $N_{i,t}^{Inv}$ is the amount of investments that lenders make on a platform *i* at week *t*; $CN_{i,t}^{Lender}$ and $CN_{i,t}^{Borrower}$ are, respectively, the cumulative numbers of lenders and borrowers in the past four weeks (from the week of t-3 to t), which proxy for the active numbers of lenders and borrowers at week t, respectively. b_1 is the borrowers' CNE NE_i^B and c_1 is the lenders' CNE NE_i^L, both calculated over a rolling window of 52 weeks.

Table 6 reports both borrowers' and lenders' CNEs using the first-year window of all platforms. The average CNEs for both borrowers and lenders are around 0.25, with a standard deviation of around 0.08. More than 70% of CNEs are positive and less than 30% are negative for both CNEs. Table 9 shows both borrowers' and lenders' CNEs during the failing period, i.e. one year before platforms fail. The average borrowers' and lenders' CNEs are 0.17 and 0.11, respectively, with a small standard deviation of 0.035 and 0.028. Overall, it indicates that both the borrowers' or lenders' CNEs are important not only for the growing episode but also during the failing period. This

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[10] Note that the trading number on the same side with one period lag can also be considered as the degree of participants in the same side, therefore, its corresponding coefficient proxies the "direct" network effect.
[11] Note that for a certain platform, if the investment amounts per lender are all missing, we use investment per loan instead, given that they are highly correlated.

answers the "chicken-and-egg" paradox in the P2P platforms, i.e. both the chicken (borrower) and the egg (lender) are important.

Turning to the "same-side" network effect of platforms, Table 6 shows that the average serial correlations for lenders' and borrowers' numbers are 0.24 and 0.23, respectively, with a standard deviation of 0.05 for both. This indicates positive same-side network effects for both the borrowers and lenders at the inception of platforms. Bellefamme et al. (2019) show that social learning coupled with positive network effects can explain how positive funding dynamics spill over from one project to another, leading to increased future backers. Informational externalities between lenders similarly lead to such same-side network effects (e.g., Zhang and Liu, 2012). We note that such social learning or lenders' herding also encourages borrowers to join the platform and thus provides a micro-foundation for our lenders' CNE.

Even though we document same-side network effects, we follow the literature of two-sided markets to focus on CNEs (Armstrong 2006; Rochet and Tirole 2003, 2006 et al.). Figure 3 plots the average CNEs of borrowers and lenders over the lifetime of both live and failed P2P platforms. We find two stylized facts. First, the CNEs of live platforms are higher than that of the failed ones starting as early as the second year. As mentioned before, platforms with larger CNEs tend to have a higher growth rate in the expansion period (first year) of a platform than those with smaller network effects. In a competing market, platforms with large CNEs tend to outperform their peers in terms of platform scale, and hence have better performances. It is thus rational for entrepreneurs to work hard in order to boost the CNEs in the platform's infancy. In contrast, failed platforms have a lower but "stable" CNEs in the first 2 years. A smaller CNE and hence platform scale may well explain a platform's failure. This indicates that an early stage CNE crucially influences the evolution of a platform.

Second, we find a downward trend in both borrowers' and lenders' CNEs in the first 2 years that then smooths out. This informs that live platforms normally experience a large growth in the early stage. Meanwhile, the borrowers' CNEs of failed platforms increase significantly after 2.5 years; the lenders' CNEs only increase slightly after 2.5 years. We explain this pattern by showing that the borrowers' CNEs are much larger than the lenders' CNEs during the platform failure period, which the next subsections elaborate.

b. Determinants of Network Effects

In this section, we analyze the determinants of CNEs for the takeoff period (first year after launch) and failing period (last year before failure). We run a cross-sectional regression:

$$NE_i^{B,L} = b_0 + b_1 DSOE_i + b_2 \log(GDP_i) + b_3 \log(Population_i) + \sum_j^T k_j LY_j(i) + u, \quad (8)$$

where NE_i^{player} is either the CNE for borrowers (NE_i^B) or lenders (NE_i^L), $DSOE_i$ is a dummy variable that equals 1 when the i^{th} platform is invested or owned by a state-owned enterprises (SOE), $LY_j(i)$ is a dummy variable that equals 1 if the i^{th} platform was launched in year j, and $\log(GDP_i)$ and $\log(Population_i)$ are the log value of GDP and population of a city where the platform is located, respectively.

Panel A of Table 7 shows that in the take-off period, the endorsement of SOE has a significantly positive influence on the borrower's CNE: An extra new borrower tends to attract more lenders in the SOE-invested platforms than those without SOE investment. This is consistent with Jiang, Liao, Wang and Zhang (2018) in that SOE-invested platforms can attract more investors. On the other hand, the lenders' CNE does not depend on the endorsement of SOEs because borrowers are on the receiving end and do not worry about a platform's reputation once they have taken loans. The population in the city where a certain platform is located influences both the borrowers' and lenders' CNEs in the take-off period of the platform, potentially due to investor home-bias and better information networks in larger cities, but logGDP does not.[12]

On the contrary, none of the factors including endorsement of SOE, logGDP and log population has any significant impact on the CNEs in the failing periods of platforms. Only the year for platform launch matters.

[12] In theory, investors can come from all over the country, however, due to the home bias documented in, for example, Coval and Moskowitz (1999), P2P investors like to invest on local platforms.

c. Asymmetries and Properties of Network Effects

As CNE is the elasticity of one-side player on the trading volume of the other side by definition, it can be large when the platform experiences rapid growth especially in its inception, i.e. a large number of players come to the platform; or when the platform experiences impending failure, i.e. a large number of users leave the platform. Therefore, the CNE is expected to have *nonlinear* relationship with the lifecycle of platforms. Particularly, regression (9) measures the response of borrowers' or lenders' CNEs when extra users join or leave the platforms:

$$NE_{i,t}^{Player} = b_0 + b_1 Positive\left(\Delta lnCN_{i,t}^{Player}\right) \times \Delta lnCN_{i,t}^{Player} + b_2 Negative\left(\Delta lnCN_{i,t}^{Player}\right) \times \Delta lnCN_{i,t}^{Player} + controls + CalendarYearDummy + u_{i,t+1} \quad (9)$$

where *player* is either lender or borrower, $NE_{i,t}^{Player}$ is the player's (lender's or borrower's) CNEs at the t[th] month of the i[th] platform lifetime, calculated with a one-year rolling window from $t-12$ to t months. $\Delta lnCN_{i,t}^{Player} = lnCN_{i,t}^{Player} - lnCN_{i,t-12}^{Player}$ is the change of player's cumulative number from t to t-12. $Positive(x)$ is a dummy variable which is set to 1 when x is positive and zeros otherwise; likewise, $Negative(x)$ is -1 when x is negative and zeros otherwise. t denotes the lifetime of a platform with a monthly frequency, ranging from 1 to 4 years.

The first two columns in Table 8 list the CNE results for borrowers, where we see significantly positive coefficients either when borrowers join or leave the platforms. When borrower's number rapidly increases, a newly joined borrower attracts more lenders than that in normal period, whereas when borrower's number quickly drops, a marginal leaving borrower causes more lenders leaving the platform than that in normal period. The similar coefficients (0.102 vs. 0.114) inform that the stickiness of lenders respond to the arrivals and departures of borrowers in a *symmetric* way. Figure 4 plots a V-shape between the borrower's CNE and change of borrower's number.

The third and fourth columns show significantly positive coefficients either when lenders join or leave the platforms. However, the magnitudes of the two coefficients are quite different. The coefficient in the lender's crowd-in period, 0.117, is 2.7 times to the coefficient in the lender's fast-leaving period, 0.043. Figure 4 plot the "check-shape" relationship between lender's CNE and change of lenders. Comparing to the borrower's CNE, the lender's CNE is close to that of borrower's CNE in a fast-growth period, but much less than that of borrower's CNE in a failing period. This indicates an *asymmetric* stickiness of borrowers and the first asymmetry of CNEs. Particularly, borrowers enter the platform at a similar speed as lenders in a fast-growth period, but have less incentives to leave the platform in a failing period. We explain the asymmetry in more detail in Section 5(a).

d. Network Effects across Platform Lifecycle

As mentioned in the previous section, lenders can easily enter or leave platforms, which leads to asymmetric CNEs when platforms experience rapid growth and decline. Consistent to this phenomenon, in Table 9, we group the CNEs according to the lifecycle of failed platforms into three categories: one year after the starting date (P1), the middle year (P2) and one year prior to failing (P3).[13] We then calculate the average borrowers' and lenders' CNEs in three periods in Table 9. For borrowers' CNEs, the difference between the starting and failing period is quite small and statistically insignificant (as shown in the t-statistics). This finding is also consistent with the first plot of Figure 3, where the borrowers' CNEs for the failed platforms exhibits a symmetric U-shaped pattern, i.e. they are large both during the take-off and during the failing periods.

In contrast, the lenders' CNEs are more than 1/3 lower in the failing year relative to their starting year. This is consistent with the notion that borrowers do not usually have incentives to leave the platform, hence borrowers remain sticky. This explains why in the second plot of Figure 3 we do not see a clear increase beyond 2.5 years of a platform's age.

[13] Middle year is chosen as a half year before the middle point of a platform's life to a half year after.

Overall, since lenders' CNEs are different in periods of growth and decline, it should have predictive power on platform growth and failure, i.e. a large lenders' CNE is likely to go together with fast platform growth period and hence a low likelihood of failure. Yet borrowers' CNEs do not have these predictions because of free entry and departure by lenders.

e. Predictability of Network Effects

We now formally analyze the predictability of CNEs on platform scale and its likelihood of failure. We firstly perform a Fama-Macbeth regression:

$$\Delta lnV_{i,t+1} = b_0 + b_1 NE^{B}_{i,t} + b_2 NE^{L}_{i,t} + b_3 lnV_{i,t} + controls + CalendarYearDummy + u_{i,1}, \quad (10)$$

where $\Delta lnV_{i,t+1}$ is the change of log trading volume at the t+1 month of the ith platform. $NE^{L}_{i,t}$ and $NE^{B}_{i,t}$ denotes the lenders' and borrowers' CNEs, respectively, calculated with one-year rolling window.

Panel A of Table 10 shows the regression results. Lenders' CNE has a positive and significant influence on the platform scale of the next month. This effect is consistently positive for all specifications in Panel A. Column 1 demonstrates that the borrowers' CNE has a small significant positive impact on the future platform scale. However, when putting these two types of CNEs in one regression, as in Columns 3, the coefficient on the borrowers' CNE changes the sign to become negative. Therefore, only the lenders' CNE can predict future platform scale consistently. A larger lenders' CNE implies positive growth of the platform, one standard deviation increase in lenders' CNEs forecasts a 1.12% increase in platform scale the next month (more than 13% in an annual basis). This finding echoes the result of the previous subsection: borrowers are sticky, but lenders are not. Therefore, lenders' CNE has an asymmetric impact on platform scale in terms of absolute value for scenarios of platform growth and decline respectively; whereas borrowers' CNE instead has a symmetric effect more or less. This is also the reason why lenders' CNE has predictive power for future platform scale, but borrowers' does not --- the second asymmetry of CNEs in predicting platform survival.

As the next step, we go on to run a direct predictive Fama-MacBeth regression for the failure of platforms:

$$F_{i,t+1} = c_1 NE_{i,t}^{L} + c_2 NE_{i,t}^{B} + c_3 lnV_{i,t} + controls + CalendarYearDummy + u_{i,t+1} \tag{11}$$

Panel B of Table 10 demonstrates that the lenders' CNEs together with platform scale can strongly predict the platform's failure in both OLS and Logit regressions. A larger lenders' CNE implies a lower rate of platform failure. For example, one standard deviation increase in lenders' CNE tends to forecast a 0.43% decrease in failure probability next month, which corresponds to a 5% decrease on an annualized basis. This is consistent with Section 4(c) in that distressed platform normally exhibit lower lenders' CNEs than growing platforms do: lenders' CNEs are important in forecasting the survival of P2P platforms due to the first asymmetry in lenders' CNEs during platforms' rises and declines.

f. Robustness Tests

We perform robustness tests with alternative specifications in this section. In Table 11, we firstly perform robustness tests using the Fama-MacBeth regression with platforms lined up by calendar times instead of lifetime. Specifically, we re-run the regression of scale on CNEs:

$$\Delta lnV_{i,t+1} = b_0 + b_1 NE_{i,t}^{B} + b_2 NE_{i,t}^{L} + b_3 lnV_{i,t} + controls + \sum_j^T k_j T_j(i,t) + u_{i,t+1} \tag{12}$$

where $T_j(i,t)$ is an age dummy, when the calendar time t of the ith platform is in the age year j, $Y_j(i,t)$ is set to 1 and otherwise 0; particularly, j is grouped as $[1,2,3,4,5,>5]$. t is indexed by calendar time at a monthly frequency from January 2015 to June 2018 (42 regressions). The final coefficients are estimated by taking the mean of the time series with the standard deviations adjusted by the Newey-West method with 42 lags. As shown in Panel A of Table 11, the asymmetric impact of lenders' CNE on platform scale still holds in regressions of this section, i.e. mainly the lenders' CNE is the key predictor, but not the borrowers' CNE.

In Panel B of Table 11, we re-run the predictive regression of platform failure with platforms lined up by calendar time:

$$lnF_{i,t+1} = b_0 + b_1 NE_{i,t}^{L} + b_2 NE_{i,t}^{B} + b_3 lnV_{i,t} + controls + \sum_j^T k_j T_j(i,t) + u_{i,t+1} \tag{13}$$

Panel B of Table 11 shows that larger lenders' CNEs result in a reduction of a platform's future failure rate, which is statistically significant at the 1% level for both the OLS and Logit regressions. In sum, findings from previous subsections are robust to alternative specifications as shown in Table 11.

5. Discussions and Implications

In this section we discuss the economic mechanisms for the asymmetric CNEs documented in Section 4. We then discuss their implications and relevance for platform owners, investors and borrowers, and regulators. These are important for the marketplace lending industry because the operation and regulation of FinTech platforms differ substantially from those of many other platforms.

a. Asymmetries and the Importance of Lenders vs. Borrowers

We explain the two asymmetries of CNEs discussed in Section 4 as reflections of screening, contracting and agency frictions, as well as inherent differences between the two sides of the market. Particularly, lenders can easily enter or leave the P2P platform, i.e. they normally do not face large contractual friction. Diversification of platform risks also drives them to multihome. This explains why borrowers' CNEs have a V-shape relation with the change of borrowers' number, i.e. when a large number of borrowers enter into the platform, a large number of lenders then come, resulting in a large borrowers' CNE. Meanwhile, when a large number of borrowers leave the platform, lenders are also free to leave, which also causes a large borrowers' CNE. This is consistent with Figure 4 that depicts a V-shaped relationship of borrowers' CNE vs. its scale changes.

In contrast, after borrowers come to a particular P2P platform to seek financing, they do not easily leave the platform because of the substantial reputation and screening cost of switching. For example, if a borrower leaves a platform, he/she might lose his/her credit or reputation on the platform (Burtch et al., 2014), which tends to be quite important in a country like China with underdeveloped credit reference system for individuals. Moreover, comprehensive background checks about the project and borrower are conducted on borrowers, including credit screening, bankruptcy history check, etc., that usually takes more than one month to complete. When the borrower leaves the platforms, he/she has to go through the same screening process one more time. Informational frictions about a borrowers' type thus imply borrowers are less willing to depart from the declining platform. That is, projects face a much larger financial friction so as not to be able to switch platforms easily.

These frictions could shed lights on the asymmetry in the lenders' CNE. When lenders' number declines, projects and borrowers tend to wait longer at the current P2P platform due to a non-trivial switching cost. This explains the asymmetric (or check shape) relationship between lenders' CNEs and change in lenders number, which shows a "check" shape in Figure 4. Such frictions of borrowers generate "stickiness" for borrowers having arrived at a platform. In fact, the "stickiness of borrowers" is beneficial for a platform ex post in that large exodus can be mitigated to some extent when experiencing negative shocks regarding lenders.

In short, borrowers are more important than lenders for P2P platforms due to their stronger stickiness. Borrowers respond less when lenders are leaving than when lenders are joining the platform because are on the receiving side and are less concerned with platform failures because they benefit if the platform no longer pursues them for paybacks. Table 12 illustrates this phenomenon by listing the change of log-numbers of borrowers or lenders before platform failures where the borrower's values are larger than the lender's for every month. On average, the monthly difference of log number changes between borrowers and lenders is 3% with a t-stat around 3.5, which corresponds to a 18% difference in the half year before failure.

Because the quality of lenders is not key to financial transactions (a dollar is a dollar no matter whom it comes from), when lenders see a positive or negative change in the number of borrowers at a platform, they can adjust their adoption of this platform quickly. However, borrowers are much stickier than lenders on such financial platforms, that is, borrowers stabilize platforms especially during platform failing periods. Under fierce competition in this emerging industry, *the acquisition of borrowers is the key to P2P platform survival*. Our empirical finding is consistent with real-life practice in that crowdfunding platforms often exempt borrowers' service fees or partner with institutions and associations to encourage project/loan listings.[14]

b. Early Prediction of Platform Failure

Now that CNEs have been found to be predictive of future scales and failure rates of platforms, we ask whether early-stage CNEs can directly predict platform failure or not. Specifically, we examine how the CNEs during the first year of a platform launch affect the default rate in its future life by performing the following regression:

$$F_{i,1} = b_0 + b_1 NE_{i,0}^B + b_2 NE_{i,0}^L + b_3 lnV_{i,0} + b_4 I_{i,0} + b_5 lnLS_{i,0} + b_6 lnIA_{i,0} + u_{i,1}, \tag{15}$$

where $NE_{i,0}^L$ and $NE_{i,0}^B$ are the lenders' and borrowers' CNEs calculated for the first year of the ith platform. Variables $lnV_{i,0}$, $I_{i,0}$, $lnLS_{i,0}$ and $lnIA_{i,0}$ are log trading volume, interest rates, log loan size and log investor's amount averaged within the first year of the ith platform, respectively. $F_{i,1}$ is a dummy variable, which is set to 1 when the ith platform failed after the first year until the end of observation period and 0 otherwise. We use both the OLS and logit method to estimate our regressions.

We also analyze the life span of platforms using a Cox hazard model as specified by Equation (16). In particular, we assume the hazard rate $h_{i,1}$ of the ith platform after the first year is as follows:

$$h_{i,1} = b_0 + b_1 NE_{i,0}^L + b_2 NE_{i,0}^B + b_3 lnV_{i,0} + b_4 I_{i,0} + b_5 lnLS_{i,0} + b_6 lnIA_{i,0} + u_{i,1}$$

[14] For example, Sundance film festival routinely invites selected films to partially raise funds through Kickstarter (Viotto, 2015).

(16)

Table 13 reports the results. It is somewhat surprising that lenders' CNE in the first year has such strong predicting power of future failures. If a platform has a large lenders' CNE at the very beginning of its life, it likely faces a relatively low failure rate during its whole lifetime. This is consistent with previous findings in Section 4 in that platforms with abilities to attract more borrowers are likely to survive due to borrowers' greater stickiness. This predictive ability is statistically significant and robust to OLS, Logit, and Cox regressions. From the OLS regression, we know that one standard deviation increase in lenders' CNE decreases 7.3% of the probability of platform failure. In contrast, borrowers' CNE does not have such a predictive capability. We find one standard deviation increase of scale tends to decrease the probability of failure by 12.9%, which is consistent with our earlier discussion in Sections 3. High interest rates, as a reflection of low loan quality, also foretell a higher failure rate in the future.

If lenders' CNEs on platform scale and future performance are persistent and consequential, the asymmetry between the cases of expansion and decline of platforms implies a bias towards platform growth. That is, the tendency to grow in scale is stronger than the tendency to shrink, if positive and negative shocks to the number of lenders occur exogenously with equal probabilities. Together with our findings in Section 3 that a larger platform tends to have a lower failure rate, the degree of asymmetry within the lenders' CNE would eventually affect the survival of a platform in its future life.

In a sense, a platform has its destiny at birth, given its initial lenders' CNE, platform scale, and interest-setting protocols. As such, examining the characteristics and performance of a newborn platform at birth can provide very valuable information for regulators and investors. If a P2P lending platform at birth is unlucky to have a small lenders' CNE, its future failure is more likely. A low trading volume at the beginning also foretells a high rate of failure. As a signal of low-quality loans, a high interest rate in a P2P platform when it is initially launched also likely raises its future probability of failure. Moreover, as Section 4(b) reveals, the platform characteristic that is most correlated with the initial lenders' CNE is the home city population rather than other factors such as state ownership.

c. Platform Competition and Relative Scale

Given the benefits of matching efficiency and risk diversification for large platforms, large platforms tend to grow even larger. Should we expect a winner-platform-takes-all outcome? After all, there seem to be significant platform consolidation in Europe and in the United States, with LendingClub and Prosper dominating the market. This is not the case in China due to entries and platform differentiation. Figure 5 shows the Herfindahl concentration index of the P2P industry in China. The concentration index trends down significantly after 2011, indicating a gradually amplified competition in the P2P industry in China.

There are several reasons for platform differentiation in China. As discussed earlier, marketplace lending in China has a much larger scale compared to other countries and the high demand and market potential lead to many entries in the industry. Different platforms may offer different forms of crowdfunding (P2P loans, equity-based, reward-based, etc.). Even within the lending market, platforms often differ in the project categories and niche. Even in the United States, Prosper caters to both personal and business loans while Funding Circle is dedicated to small- and medium-sized businesses. Some platforms require all-or-nothing implementations while others all flexible funding (see, e.g., Cong and Xiao, 2019). Locations could also play a role, to the extent that a platform can acquire information about borrowers offline more easily if the borrowers are local. Finally, platforms could differ in terms of additional services such as marketing, entrepreneurship mentoring, certification, curation, etc. At least in the nascent stage of development, the industry is populated by a large number of competitors.

Nevertheless, scale gives a platform competitive edge in the industry. In a sense, competition may lead to a massive number of failures and only a few early top platforms survive. To tackle this question, we take the percentage rank (descending) of the scale of the platform as the proxy for the relative position of the platform in the industry, and examine how the ranks influence the failure of platforms. We run the following Fama-Macbeth regression:

$$F_{i,t+1} = b_0 + b_1 Rank_{i,t} + b_2 NE^L_{i,t} + b_3 NE^B_{i,t} + b_4 lnV_{i,t} + Controls + \sum_j^T k_j T_j(i,t) + u_{i,t+1}, \qquad (14)$$

where time t is indexed by *calendar* time in a monthly frequency from January 2015 to June 2018. $Rank_{i,t}$ is the descending percentage rank on scale (trading volume), calculated as the rank of the i^{th} platform divided by the number of platforms at the same calendar time. Table 14 shows that $Rank_{i,t}$ is significantly positive in both the OLS and logit estimation, which implies that a top-ranked platform has a low default probability relative to other platforms even after controlling for absolute platform sizes. For example, suppose platform A in year 2010 and platform B in year 2012 have the same size. If the rank of platform A is 10% in 2010, and B is 20% in 2012, platform A then has smaller failure probability relative to B.

We find that holding other variables unchanged, a 10% up-shift in rank leads to a 0.42% monthly decrease in default probability, which corresponds to a 5% annualized probability. Therefore, given the large number of P2P platforms in China, top platforms do have an edge for survival relative to bottom ones not only because of their larger sizes but also because their higher ranks, consistent with the network effects for two-sided platforms. Our findings also demonstrate that both absolute scale and relative scale matter for platforms' survival.

d. Regulatory Implications

Regulating financial platforms such as P2P lending platforms presents new challenges because these platforms entail dispersed (retail) investors and borrowers, exhibit large network effects, and are subject to runs, not to mention that the business models are new and evolving that no existing regulatory policy readily apply. Because China's credit reference system is still under development, informational asymmetry regarding borrowers' credit status and default risk is severe. Private platforms' own attempts at risk management through securitization or principal guarantee further complicates regulation. These risks may spill over to traditional financial institutions and become systemic because many P2P platforms work closely with financial institutions such as trusts and insurance companies, not to mention that frauds and illegal crowdfunding in the name of financial innovation are rampant.

A better understanding of the role of platform scale and CNEs can therefore assist regulators. For example, regulators can closely monitor platforms' absolute and relative scales to anticipate platform failures. They can also disclose platform statistics such as CNEs, trading volumes, interest rates, and home city population, to alert and guide investors at a relatively early stage of platform life cycles. This is especially important in the early development of the industry when investors are mostly retail investors.[15]

6. Conclusion

Motivated by the rapid growth of FinTech marketplace lending across the globe and its massive entries and failures in emerging economies such as China, we study the determinants of platforms' evolution and industry dynamics to not only inform the theory on two-sided platforms, but also provide guidance for platform owners, retail investors, and regulator. Specifically, we measure platform scale and network effects and empirically show that a larger scale predicts a lower probability of platform failure due to better matching efficiency and a higher level of diversification. We then demonstrate that platform scale is largely related to borrowers' and lenders' cross-side network effects (CNEs), which predict platforms' future survival and failure.

Moreover, borrower's CNEs are symmetrically positive in both fast-growing and failing periods of platforms, which is caused by lenders' easy entry and departure from platforms. In contrast, lender's CNEs are asymmetric, being much smaller during declines than that during growth due to the stickiness of borrowers. Because of this asymmetry, the lender's CNEs can predict the future failure of P2P platforms, even at a very early stage. These asymmetries reflect unique features of financial platforms and

[15] Even in developed countries, crowdfunding attracts mostly retail investors (Baeck, Collins, and Zhang, 2014).

inherent differences between lenders and borrowers' objectives and risks, and frictions arising from contract incompleteness and agency issues.

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Tables

Table 1. Data Description

We have a total of 988 platforms, among them 418 (42.3%) fail, 570 (57.7%) operated up to June of 2018. Our data is in weekly frequency. In Panel A, we compute the average life-spans and standard deviations for live and failed platforms, respectively. In Panel B, we compute some basic features for live and failed P2P platforms. The trading volume, investment size, loan size, the amount per borrower, the amount per lender are in the unit of RMB 10,000.

Panel A: Starting Years of P2P Platforms

Starting Year	2011 and before	2012	2013	2014	2015	2016	2017 and after	Total
Total No.	13	37	141	465	255	66	11	988
Live	11	21	53	234	181	59	11	570
Failed	2	16	88	231	74	7	0	418
Average Life Span (Live)	7.7	5.6	4.7	3.7	3.0	2.1	1.3	3.5
Average Life Span (Failed)	4.9	3.3	2.4	2.1	2.0	1.5	--	2.2

Panel B: Basic Features of P2P Platforms

	Mean(all)	Std(all)	Mean (live)	Std(live)	Mean(fail)	Std(fail)
Trading Volume (log)	5.964	1.720	6.643	1.675	5.039	1.298
No. Investment (log)	5.209	1.782	5.777	1.914	4.455	1.238
No. Loan (log)	2.721	1.488	3.160	1.617	2.123	1.026
No. Lender (log)	4.820	1.678	5.325	1.807	4.151	1.201
No. Borrower (log)	2.583	1.571	3.178	1.780	1.905	0.898
Interest Rate	0.136	0.039	0.117	0.029	0.161	0.036
Loan Size (log)	2.857	1.075	3.051	1.093	2.592	0.993
Investment Size (log)	0.369	0.838	0.450	0.863	0.263	0.792
Origination Time (log)	9.596	2.459	8.951	2.573	10.455	2.002
No. of Loans per Borrower (log)	0.288	0.391	0.350	0.455	0.217	0.286
No. of Investments per Lender (log)	0.389	0.339	0.453	0.391	0.304	0.230
Amount per Borrower (log)	3.045	1.171	3.262	1.259	2.798	1.007
Amount per Lender (log)	0.758	0.846	0.902	0.833	0.567	0.825
Loan Concentration	69.3%	28.8%	57.6%	30.7%	81.6%	20.4%
Investment Concentration	49.7%	23.0%	46.7%	23.3%	56.8%	20.7%

Table 2. Scale and Platform Features

We first sort all platforms into two groups according to their scale, and then calculate average features for the two groups and their difference.

	Large Platform	Small Platform	Difference	t-stats of Difference
Trading Volume (log)	6.822	4.329	2.493	36.014
No. Investment (log)	6.369	4.062	2.307	26.453
No. Loan (log)	3.529	1.909	1.620	20.385
No. Lender (log)	5.893	3.760	2.133	25.616
No. Borrower (log)	3.434	1.745	1.689	16.951
Interest Rate	0.122	0.150	-0.029	-12.371
Loan Size (log)	3.292	2.420	0.872	13.939
Investment Size (log)	0.474	0.266	0.208	3.894
Origination Time (log)	8.880	10.308	-1.428	-9.422
No. of Loans per Borrower	0.385	0.193	0.192	6.737
No. of Investments per Lender	0.476	0.303	0.173	8.229
Amount per Borrower	3.509	2.588	0.920	11.361
Amount per Lender	0.950	0.568	0.382	7.218
Loan Concentration	57.6%	82.4%	-24.8%	-9.521
Investment Concentration	39.6%	64.0%	-24.4%	-16.715

Table 3. Scale and Platform Failure

In this table, we analyze the relationship between scale and platform failure by running the following Fama-MacBeth regression:

$$F_{i,t+1} = b_0 + b_1 lnV_{i,t} + b_2 I_{i,t} + b_3 lnLS_{i,t} + b_4 lnIA_{i,t} + \sum_j^T k_j Y_j(i,t) + u_{i,t+1},$$

where $F_{i,t+1}$ is a dummy variable, which is set to 1 when the i^{th} platform failed at the $t+1^{th}$ month and 0 otherwise; $lnV_{i,t}$ is the average log trading volume (in the unit of RMB 10,000) of the i^{th} platform at month t, $I_{i,t}$ is the average interest rates at t^{th} month across all projects on the i^{th} platform, $LS_{i,t}$ is the average loan size for borrowers on the i^{th} platform at month t, $IA_{i,t}$ is the average investment amount for lenders on the i^{th} platform at month t. t is indexed by the lifetime of a platform with a monthly frequency, from 1 to 4 years (36 months). $Y_j(i,t)$ is a calendar year dummy, when the lifetime t of the i^{th} platform is in the calendar year j, $Y_j(i,t)$ is set to 1 and otherwise 0. Specifically, j takes for following range: 2012 and before, 2013, 2014, 2015, 2016, 2017 and after. At each time t, we run a cross-sectional regression for all living platforms; and then obtain a time series of coefficients for all time. The final coefficients are estimated by taking the mean of the time series with the standard deviations adjusted by the Newey-West method with 36 lags. Quantities in brackets are the t-statistics. We use both OLS and logit model to perform regressions, respectively. For brevity, we omit to present the estimation of calendar time dummies.

	OLS		**Logit**	
$lnV_{i,t}$	-0.010	-0.010	-0.269	-0.281
	(-27.187)	(-17.241)	(-5.082)	(-6.485)
$I_{i,t}$		-0.134		0.100
		(-1.268)		(0.053)
$lnLS_{i,t}$		-0.002		0.005
		(-2.329)		(0.253)
$lnIA_{i,t}$		0.002		0.049
		(1.650)		(3.326)
Calendar Year Dummy	Yes	Yes	Yes	Yes
$\mathbf{R^2}$	2.1%	2.7%	2.5%	3.2%

Table 4. Platform Scale and Matching Efficiency

This table reports the relationship between matching efficiency of platforms and their scale by running the following regression:

$$lnM_{i,t+1} = d_0 + d_1 lnV_{i,t} + d_2 I_{i,t} + d_3 lnLS_{i,t} + d_4 lnIA_{i,t} + \sum_j^T k_j Y_j(i,t) + u_{i,t+1}$$

where $M_{i,t+1}$ is the average origination time (in seconds) that a project has achieved its full-scale amount on the i^{th} platform at the $t+1^{th}$ month. t is indexed by the lifetime of a platform with a monthly frequency, from 1 to 4 years. $Y_j(i,t)$ is a calendar year dummy, when the lifetime t of the i^{th} platform is in the calendar year j, $Y_j(i,t)$ is set to 1 and otherwise 0. Specifically, j takes for following range: 2012 and before, 2013, 2014, 2015, 2016, 2017 and after. The final coefficients are estimated by taking the mean of the time series with the standard deviations adjusted by the Newey-West method with 36 lags. Quantities in brackets are the t-statistics.

$\boldsymbol{lnV_{i,t}}$	-0.597	-0.868
	(-7.433)	(-13.483)
$\boldsymbol{I_{i,t}}$		-9.267
		(-12.473)
$\boldsymbol{lnLS_{i,t}}$		1.196
		(11.104)
$\boldsymbol{lnIA_{i,t}}$		-0.242
		(-6.428)
Calendar Year Dummy	Yes	Yes
$\mathbf{R^2}$	15.9%	31.3%

Table 5. Platform Scale and Risk Diversification

We run a Fama-MacBeth regression to estimate the relationship between the platform scale and its future concentration:

$$C_{i,t+1} = d_0 + d_1 lnV_{i,t} + d_2 I_{i,t} + d_3 lnLS_{i,t} + d_4 lnIA_{i,t} + \sum_j^T k_j Y_j(i,t) + u_{i,t+1}$$

where $C_{i,t+1}$ is the percentage of top 10 investment in the i^{th} platform at the $t+1^{th}$ month of its lifetime. t is indexed by the lifetime of a platform with a monthly frequency, from 1 to 4 years (36 months). $Y_j(i,t)$ is a calendar year dummy, when the lifetime t of the i^{th} platform is in the calendar year j, $Y_j(i,t)$ is set to 1 and otherwise 0; particularly, j is grouped as $[\leq 2012, 2013, 2014, 2015, 2016, \geq 2017]$. The final coefficients are estimated by taking the mean of the time series with the standard deviations adjusted by the Newey-West method with 36 lags. Quantities in brackets are the t-statistics.

	Investment Concentration		**Loan Concentration**	
$\boldsymbol{lnV_{i,t}}$	-0.093	-0.101	-0.083	-0.103
	(-90.302)	(-68.422)	(-23.786)	(-26.213)
$\boldsymbol{I_{i,t}}$		-0.076		-0.231
		(-2.004)		(-6.609)
$\boldsymbol{lnLS_{i,t}}$		-0.034		0.102
		(-40.826)		(33.924)
$\boldsymbol{lnIA_{i,t}}$		0.148		0.039
		(172.577)		(15.907)
Calendar Year Dummy	Yes	Yes	Yes	Yes
$\mathbf{R^2}$	43.5%	65.5%	25.3%	42.9%

Table 6. The Measurement of Network Effects

This table reports the measurement of network effects, i.e. the elasticity of investment (loan) numbers with respect to the "active" lenders (borrowers). We perform the following two regressions:

$$lnN_{i,t+1}^{Inv} = b_0 + b_1 lnCN_{i,t}^{Borrower} + b_2 lnN_{i,t}^{Inv} + b_3 I_{i,t} + b_4 lnLS_{i,t} + b_5 lnIA_{i,t} + u_{i,t+1} \quad (1)$$

$$lnN_{i,t+1}^{Loan} = c_0 + c_1 lnCN_{i,t}^{Lender} + c_2 lnN_{i,t}^{Loan} + c_3 I_{i,t} + c_4 lnLS_{i,t} + c_5 lnIA_{i,t} + u_{i,t+1} \quad (2)$$

where $N_{i,t}^{Inv}$ and $N_{i,t}^{Loan}$ are the number of investments and loans at the t[th] week of platform i's lifetime, respectively; $CN_{i,t}^{Lender}$ and $CN_{i,t}^{Borrower}$ are the cumulative numbers of lenders and borrowers in the past four weeks (from the week of t-3 to t). $I_{i,t}$, $lnLS_{i,t}$ and $lnLA_{i,t}$ are interest rates, log loan size and log investing amount averaged within the t[th] month on the i[th] platform, respectively. b_1 stands for the borrowers' CNE NE_i^B, and c_1 stands for the lenders' CNE NE_i^L, both calculated by a rolling one-year window. The following table shows the statistics of network effect using the first-year data. The correlation between borrowers' and lenders' CNEs is 0.54.

	Borrowers' Network Effect	Lenders' Network Effect	Serial Corr (Lenders' Numbers)	Serial Corr (Borrowers' Numbers)
Average	0.257	0.243	0.240	0.226
St Dev	0.483	0.387	0.324	0.312
Max	2.318	1.701	1.317	1.168
Min	-1.489	-1.178	-0.632	-0.784
Positive (%)	70.6%	73.9%	76.8%	76.3%
Negative (%)	29.4%	26.1%	23.2%	23.7%
Positive with 95% significance (%)	24.7%	26.6%	30.7%	27.8%
Negative with 95% significance (%)	2.6%	1.1%	0.9%	0.7%
Non-significance (%)	72.7%	72.3%	68.5%	71.4%

Table 7. Determinants of Network Effects

In this table, we analyze the determinants of the network effects for the take-off period (first year after launch) and failing period (last year before failure). We run a cross-sectional regression:

$$NE_i^{B,L} = b_0 + b_1 DSOE_i + b_2 \log(GDP_i) + b_3 \log(Population_i) + \sum_j^T k_j LY_j(i) + u$$

where $NE_i^{B,L}$ is the borrowers' (NE_i^B) or lenders' (NE_i^L) CNEs, $DSOE_i$ is a dummy variable that equals 1 when the i^{th} platform is invested by state-owned enterprises, $LY_j(i)$ is a dummy variable that equals 1 if the i^{th} platform was launched in year j, and $\log(GDP_i)$ and $\log(Population_i)$ are the log value of GDP and population of a city where the platform is located, respectively. Quantities in brackets are the t-statistics.

Panel A: Determinants of First-Year Network Effects

	Borrowers CNE	**Lenders' CNE**
$\boldsymbol{DSOE}$	0.203	0.021
	(2.648)	(0.343)
$\mathbf{log}(\boldsymbol{GDP})$	0.066	0.038
	(1.284)	(0.922)
$\mathbf{log}(\boldsymbol{Population})$	0.088	0.080
	(2.799)	(3.157)
Launch Year Dummy	Yes	Yes
$\mathbf{R^2}$	3.64%	3.33%

Panel B: Determinants of Last-Year (before failure) Network Effects

	Borrowers' CNE	**Lenders' CNE**
$\boldsymbol{DSOE}$	-0.211	-0.210
	(-1.185)	(-1.384)
$\mathbf{log}(\boldsymbol{GDP})$	0.010	0.009
	(0.135)	(0.150)
$\mathbf{log}(\boldsymbol{Population})$	0.012	0.023
	(0.259)	(0.565)
Launch Year Dummy	Yes	Yes
$\mathbf{R^2}$	2.10%	4.14%

Table 8. Asymmetry of Cross-side Network Effects

In this table, we run a Fama-Macbeth regression to find the asymmetric properties of CNEs:

$$NE_{i,t}^{Player} = b_0 + b_1 Positive(\Delta lnCN_{i,t}^{Player}) \times \Delta lnCN_{i,t}^{Player} + b_2 Negative(\Delta lnCN_{i,t}^{Player}) \times \Delta lnCN_{i,t}^{Player} + controls + CalendarYearDummy + u_{i,t+1}$$

where player is either lender or borrower, $NE_{i,t}^{Player}$ is the player's (lender's or borrower's) CNEs at the t[th] month of the i[th] platform lifetime, calculated with a rolling one year window from $t-12$ to t months. $\Delta lnCN_{i,t}^{Player} = lnCN_{i,t}^{Player} - lnCN_{i,t-12}^{Player}$ is the change of player's cumulative number from t to t-12. $Positive(x)$ is a dummy variable which is set to 1 when x is positive and zeros otherwise; likewise, $Negative(x)$ is -1 when x is negative and zeros otherwise. t denotes the lifetime of a platform with a monthly frequency, ranging from 1 to 4 years (36 regressions as we start from the end of the first year). The final coefficients are estimated by taking the mean of the time series with the standard deviations adjusted by the Newey-West method with 36 lags. Quantities in brackets are the t-statistics.

	$NE_{i,t+1}^{B}$		$NE_{i,t+1}^{L}$	
$Positive(\Delta lnCN_{i,t}^{Borrower}) \times \Delta lnCN_{i,t}^{Borrower}$	0.102	0.102		
	(4.576)	(5.152)		
$Negative(\Delta lnCN_{i,t}^{Borrower}) \times \Delta lnCN_{i,t}^{Borrower}$	0.112	0.114		
	(13.266)	(16.021)		
$Positive(\Delta lnCN_{i,t}^{Lender}) \times \Delta lnCN_{i,t}^{Lender}$			0.116	0.117
			(46.896)	(41.995)
$Negative(\Delta lnCN_{i,t}^{Borrower}) \times \Delta lnCN_{i,t}^{Borrower}$			0.040	0.043
			(7.441)	(8.133)
Controls	No	Yes	No	Yes
Calendar Year Dummy	Yes	Yes	Yes	Yes
R^2	7.3%	8.1%	6.6%	6.0%

Table 9. Lifecycle Network Effects

In this table, we group the CNEs according to the lifecycle of *failed* platforms into three categories: one year after their starting dates (P1), the middle one year (P2) and one year before failed dates (P3). We then calculate the average borrowers' and lenders' CNEs in these three categories. Quantities in square brackets are standard deviations.

	One Year after the Starting Date (P1)	**The Middle One Year (P2)**	**One Year before the Failed Date (P3)**	**Diff (P3-P1)**
Borrowers'	0.153	0.136	0.172	0.018
Network Effect	[0.029]	[0.030]	[0.035]	[0.042]
Lenders'	0.172	0.154	0.110	-0.062
Network Effect	[0.022]	[0.027]	[0.028]	[0.031]

Table 10. Predictability of Network Effects

In this table, we analyze the predictability of CNEs on platform scale and failures. Specifically, in Panel A, we do the following two Fama-Macbeth regression:

$$\Delta lnV_{i,t+1} = b_0 + b_1 NE_{i,t}^{B} + b_2 NE_{i,t}^{L} + b_3 lnV_{i,t} + Controls + CalendarYearDummy + u_{i,1} \quad (1)$$

$$F_{i,t+1} = c_1 NE_{i,t}^{L} + c_2 NE_{i,t}^{B} + c_3 lnV_{i,t} + Controls + CalenderYearDummy + u_{i,t+1} \quad (2)$$

In both Panel A and B, t is indexed by the lifetime of a platform with a monthly frequency, ranged from 1 to 4 years (36 regressions). The final coefficients are estimated by taking the mean of the time series with the standard deviations adjusted by the Newey West method with 36 lags. Quantities in brackets are the t-statistics.

Panel A: Predictability on Platform Scale

	(1)	(2)	(3)
$\boldsymbol{NE_{i,t}^{B}}$	0.009		-0.003
	(2.180)		(-0.803)
$\boldsymbol{NE_{i,t}^{L}}$		0.026	0.029
		(6.540)	(8.881)
$\boldsymbol{lnV_{i,t}}$	-0.020	-0.021	-0.020
	(-7.909)	(-9.574)	(-8.091)
Controls	Yes	Yes	Yes
Calendar Year Dummy	Yes	Yes	Yes
$\mathbf{R^2}$	3.0%	3.1%	3.4%

Panel B: Predictability on Platform Failure

Specification	**OLS**			**Logit**		
$\boldsymbol{NE_{i,t}^{B}}$	-0.002		0.002	-0.089		0.089
	(-1.194)		(0.937)	(-1.823)		(1.124)
$\boldsymbol{NE_{i,t}^{L}}$		-0.009	-0.011		-0.323	-0.389
		(-9.288)	(-7.001)		(-6.586)	(-4.734)
$\boldsymbol{lnV_{i,t}}$	-0.010	-0.010	-0.010	-0.306	-0.302	-0.301
	(-15.094)	(-13.977)	(-13.880)	(-5.447)	(-5.620)	(-5.682)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
$\mathbf{R^2}$	3.2%	3.2%	3.4%	3.7%	3.7%	4.0%

Table 11. Robustness Checks

In this table, we perform robustness checks with time t indexed by calendar times instead of a lifetime of platforms in regressions. Specifically, in Panel A, we re-run the regression of scale on the CNEs.

$$\Delta lnV_{i,t+1} = b_0 + b_1 NE_{i,t}^{B} + b_2 NE_{i,t}^{L} + b_3 lnV_{i,t} + Controls + \sum_j^T k_j T_j(i,t) + u_{i,t+1} \quad (1)$$

where $\Delta lnV_{i,t+1}$ is the change of log trading volume at the t+1 month of the i^th platform. $NE_{i,t}^{L}$ and $NE_{i,t}^{B}$ are the lenders' and borrowers' CNEs, respectively, calculated with one-year rolling window. $T_j(i,t)$ is an age dummy, when the calendar time t of the i^th platform is in the age year j, $T_j(i,t)$ is set to 1 and otherwise 0; particularly, j is grouped as $[1, 2, 3, 4, 5, > 5]$.

In Panel B, we re-run the regression of platform failure on CNEs:

$$lnF_{i,t+1} = b_0 + b_1 NE_{i,t}^{L} + b_2 NE_{i,t}^{B} + b_3 lnV_{i,t} + Controls + \sum_j^T k_j T_j(i,t) + u_{i,t+1} \quad (2)$$

In both Panel A and B, t is indexed by calendar time in a monthly frequency from January 2015 to June 2018 (42 months). At each time t, we run a cross-sectional regression for all living platforms and then obtain a time series of coefficients for t. The final coefficients are estimated by taking the mean of the time series with the standard deviations adjusted by the Newey-West method with 42 lags.

Panel A: Change of Platform Scale and Network Effects

	(1)	**(2)**	**(3)**
$\boldsymbol{NE_{i,t}^{B}}$	0.010		0.000
	(1.067)		(0.015)
$\boldsymbol{NE_{i,t}^{L}}$		0.024	0.024
		(2.291)	(2.935)
$\boldsymbol{lnV_{i,t}}$	-0.017	-0.018	-0.018
	(-4.097)	(-4.191)	(-4.460)
Controls	Yes	Yes	Yes
Age Dummies	Yes	Yes	Yes
$\mathbf{R^2}$	4.7%	4.7%	5.0%

Panel B: Platform Failure and Network Effects

	OLS			Logit		
$NE_{i,t}^{B}$	0.002		0.007	-0.057		0.196
	(1.329)		5.121	(-0.906)		(3.828)
$NE_{i,t}^{L}$		-0.008	-0.012		-0.463	-0.636
		(-2.474)	(-3.182)		(-3.634)	(-4.658)
$lnV_{i,t}$	-0.010	-0.010	-0.010	-0.499	-0.490	-0.487
	(-6.880)	(-7.003)	(-6.980)	(-14.640)	(-13.101)	(-13.649)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Age Dummies	Yes	Yes	Yes	Yes	Yes	Yes
$\mathbf{R^2}$	3.9%	4.0%	4.2%	4.9%	5.0%	5.2%

Table 12. Change of Borrower's and Lender's Numbers Before Platform Failures

This table reports the change of log numbers of borrowers and lenders up to 6 months before platform failures. Particularly, we first take the log of the average borrower's or lender's number in a certain month before platform's failure, we then take the difference to its previous month. Quantities in square brackets are standard deviations.

Months to Failure	Average Log Number changes for Borrowers	Average Log Number Changes for Lenders	Difference (Borrower - Lender)
6	-0.016	-0.043	0.028
			[0.019]
5	-0.040	-0.053	0.012
			[0.018]
4	-0.053	-0.084	0.031
			[0.020]
3	-0.077	-0.116	0.039
			[0.020]
2	-0.082	-0.112	0.030
			[0.024]
1	-0.150	-0.192	0.042
			[0.022]
Average	-0.069	-0.099	0.030
			[0.008]

Table 13. Early-stage Network Effects and P2P Platform Failure

In this table, we examine how the network effects of the first year of a platform will influence the future default in its future life by running:

$$F_{i,1} = b_0 + b_1 NE_{i,0}^{B} + b_2 NE_{i,0}^{L} + b_3 lnV_{i,0} + b_4 I_{i,0} + b_5 lnLS_{i,0} + b_6 lnIA_{i,0} + u_{i,1} \quad (1)$$

where $NE_{i,0}^{L}$ and $NE_{i,0}^{B}$ are the lenders' and borrowers' CNEs calculated from the first year of the i^th platform. $lnV_{i,0}$, $I_{i,0}$, $lnLS_{i,0}$ and $lnIA_{i,0}$ are log trading volume, interest rates, log loan size and log investor's amount averaged within the first year of the i^th platform, respectively. $F_{i,1}$ is a dummy variable, which is set to 1 when the i^th platform failed after the first year and 0 otherwise. We use both the OLS and logit regressions to estimate our regressions.

We also analyze the life span of platforms using a Cox hazard model. In particular, we assume the hazard rate $h_{i,1}$ of the i^th platform after the first year follows:

$$h_{i,1} = b_0 + b_1 NE_{i,0}^{L} + b_2 NE_{i,0}^{B} + b_3 lnV_{i,0} + b_4 I_{i,0} + b_5 lnLS_{i,0} + b_6 lnIA_{i,0} + u_{i,1} \quad (2)$$

We estimate parameters of Equation (2) in a Cox model. Quantities in brackets are the t-statistics.

	OLS	Logit	Cox
$NE_{i,0}^{B}$	-0.015	-0.057	-0.103
	(-0.358)	(-0.260)	(-0.757)
$NE_{i,0}^{L}$	-0.189	-0.989	-0.510
	(-3.731)	(-3.500)	(-2.920)
$lnV_{i,0}$	-0.075	-0.451	-0.308
	(-4.862)	(-4.796)	(-5.348)
$I_{i,0}$	4.493	24.013	10.474
	(10.968)	(9.440)	(8.763)
$lnLS_{i,0}$	0.001	0.065	-0.058
	(0.046)	(0.520)	(-0.765)
$lnIA_{i,0}$	0.029	0.173	0.118
	(1.286)	(1.365)	(1.558)
R^2	25.7%	28.3%	NA

Table 14. Competition and Platform Failure

This table analyzes in the role of competition in influencing platform failure by running the following Fama-Macbeth regression:

$$F_{i,t+1} = b_0 + b_1 Rank_{i,t} + b_2 NE^L_{i,t} + b_3 NE^B_{i,t} + b_4 lnV_{i,t} + Controls + \sum_j^T k_j T_j(i,t) + u_{i,t+1},$$

where time t is indexed by *calendar* time in a monthly frequency from January 2015 to June 2018 (42 months). $Rank_{i,t}$ is the descending percentage rank in term of scale (trading volume) of the i^th^ platform with respective to all platforms at the same calendar time. $T_j(i,t)$ is an age dummy, when the calendar time t of the i^th^ platform is in the age year j, $T_j(i,t)$ is set to 1 and otherwise 0; particularly, j is grouped as $[1,2,3,4,5,>5]$. At each time t, we run a cross-sectional regression for all living platforms; and then obtain a time series of coefficients for t. The final coefficients are estimated by taking the mean of the time series with the standard deviations adjusted by the Newey-West method with 42 lags. Quantities in brackets are the t-statistics. We use both OLS and logit model to perform regressions, respectively. For brevity, we omit to present the estimation of dummies.

	OLS		**Logit**	
$\boldsymbol{Rank_{i,t}}$	0.103	0.042	5.994	6.214
	(9.212)	(2.752)	(9.673)	(5.984)
$\boldsymbol{lnV_{i,t}}$		-0.006		-0.035
		(-4.354)		(-0.730)
$\boldsymbol{NE^B_{i,t}}$		0.007		0.244
		(5.294)		(4.085)
$\boldsymbol{NE^L_{i,t}}$		-0.012		-0.624
		(-3.096)		(-4.253)
Controls	Yes	Yes	Yes	Yes
Age Dummies	Yes	Yes	Yes	Yes
$\mathbf{R^2}$	3.7%	4.5%	4.7%	5.6%

Figures

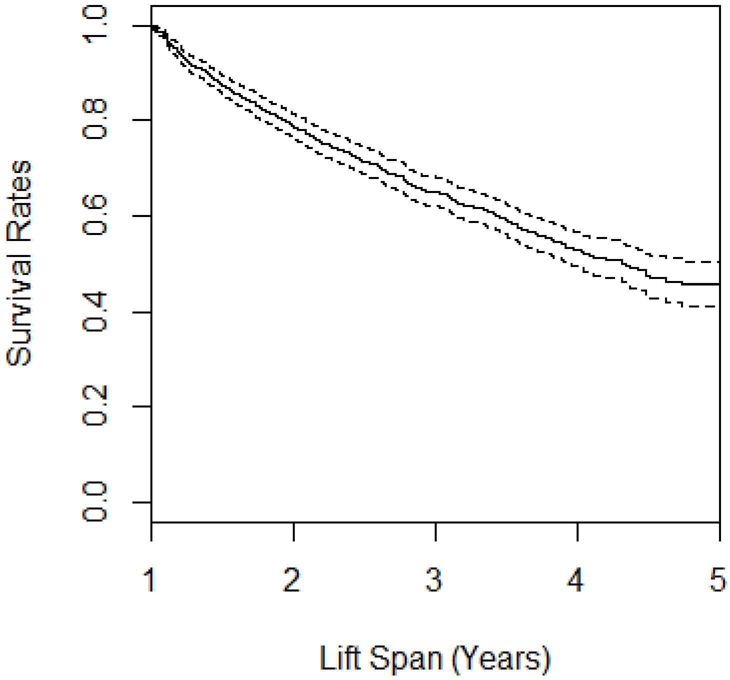

Figure 1 Kaplan-Meier Survival Rate vs. Platform Lifespan
The dotted line shows the 95% confidence levels.

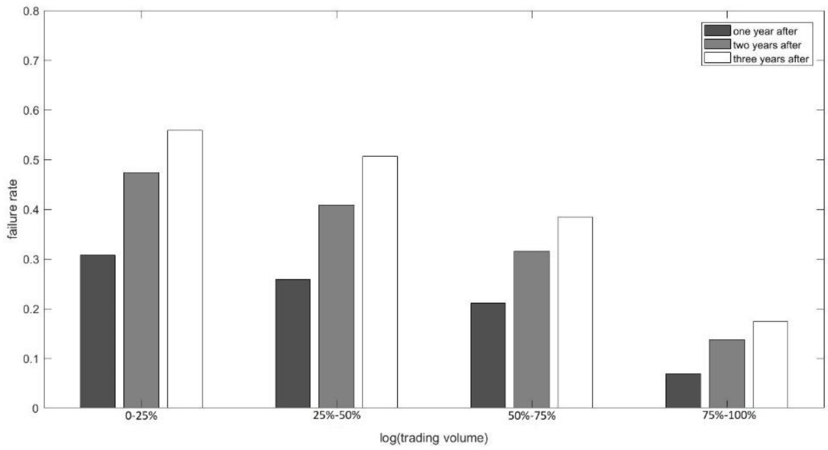

Figure 2 Trading Volume (size) in the First Year and Failure Rates afterwards.

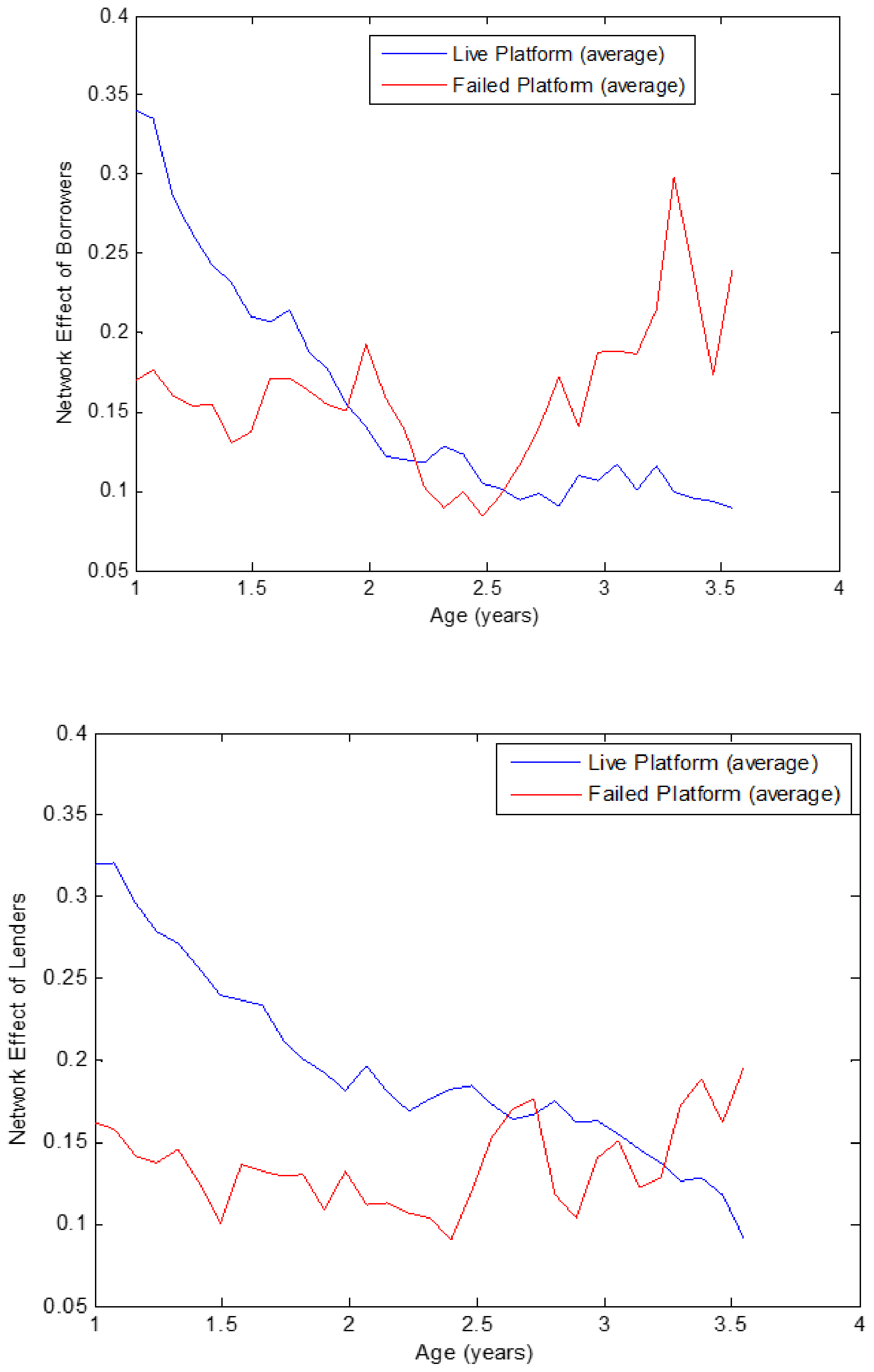

Figure 3. Network effects for borrowers and investors.

We calculate the borrowers' and lenders' CNEs by regressions with a one-year rolling window. This figure shows average CNEs for platforms of live and failed ones separately.

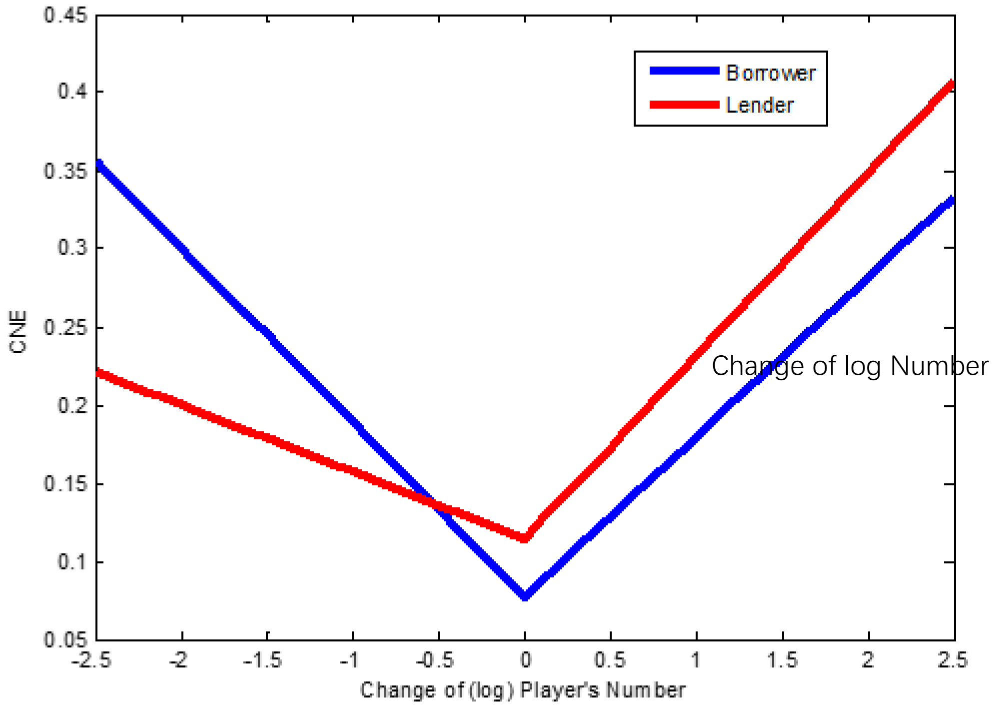

Figure 4. Network effects and Change of (log) Player's Number.

This figure is plotted based on regression coefficients in Table 8.

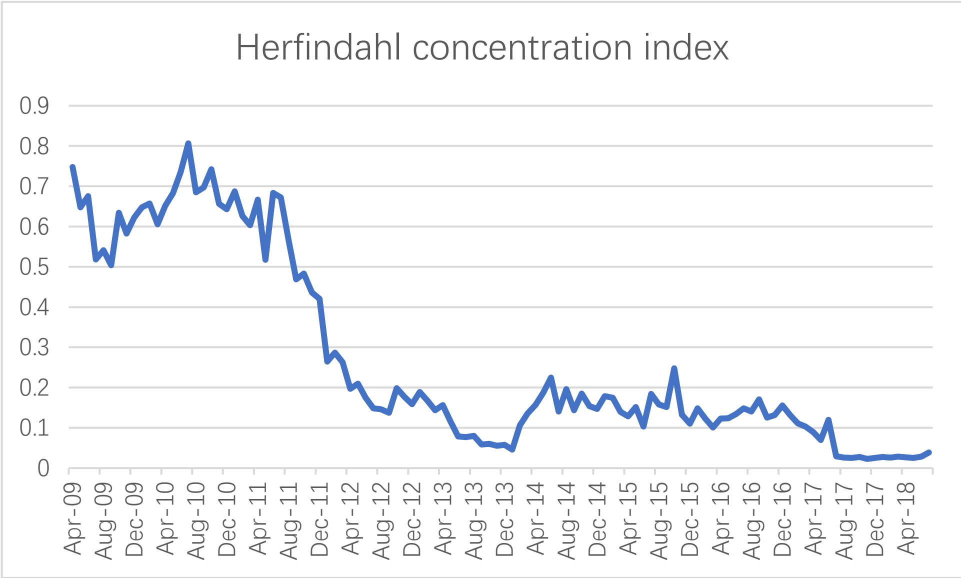

Figure 5. Herfindahl Concentration Index for Chinese P2P Markets.

Appendix A. Institutional details on P2P lending

a. A brief history of p2p lending

Peer-to-peer lending (P2P lending) is the practice of directly matching lenders and borrowers through online services, thereby cutting out traditional banking protocols. The P2P platforms do not lend their own funds but act as facilitators to both the borrower and the lender. The first company to offer P2P lending was Zopa, a UK company that has since issued more than $2.9 billion in loans since it was founded in February 2005. Since then many P2P lending platforms have emerged worldwide, with LendingClub being the biggest P2P lender in the US, having $47 billion total loans originated by 2018.[16] According to AltFi, more than $72 billion loans were originated by peer-to-peer firms in the U.S., U.K., the European Union, Australia and New Zealand in 2016.[17]

b. China's P2P history, growth, and current market size

P2P lending was first introduced in China in 2007. While having a later start than the US and UK, the Chinese P2P market has enjoyed phenomenal growth over the last ten years, and has become an important component of the financial industry. By early 2019, more than 5,000 P2P platforms had been established in China, involving about 50 million users and 1.3 trillion yuan ($195 billion) of outstanding loans, exceeded the US and UK P2P lending market combined. One potential facilitator of the rapid growth in China's P2P lending is the slack regulation when compared to the US standard. Prior to 2015, China's regulatory framework on digital finance was very preliminary. Chinese financial authorities, businesses and scholars have shared the view that there were insufficient regulations on the rapidly growing digital finance sector (Weihuan 2015).

[16] See www.lendingclub.com.
[17] See https://www.bloomberg.com/quicktake/peer-peer-lending.

Tightening regulation and cracking down of platforms that fail to meet the standard are currently undergoing. The number of platforms dropped by more than 50 percent to 1,021 during 2018 due to failing to comply with the regulations.[18] Brusa (2019) summarized three distinctive features of China's situation that catalyzed the fast growth of China's P2P lending, namely, credit rationing limited credit supply for small enterprises, a large supply of funds from retail investors, and market failure in the provision of credit. This unique environment for P2P lending resulted in the high-risk profile of the Chinese P2P industry.

c. Mechanics of China's P2P lending platform

The P2P platforms do not lend their own funds but act as facilitators to both the borrowers and the lenders. Looking at the top 5 P2P platforms of China (P2P platform surveyed: 陆金服 (101b RMB loans outstanding), 玖富普惠 (49b RMB loans outstanding), 宜人贷 (43b RMB loans outstanding), 人人贷 (33b RMB loans outstanding), 爱钱进 (32b RMB loans outstanding)), we see that most of them offer loans in three types of format: 1. Individual loans for direct investment 2. Screened out a portfolio of loans or platform's product 3. The secondary market for loans originated in the platform. Song (2018) gave a detailed outline of the operating mechanism of direct investment in individual loans. The borrowers begin by submitting their loan requests information: loan amount, loan interest rate, repayment term and date, together with personal information such as proof of identity, income and real estate ownership. Once the information is verified, the borrowers' loan request together with the certified personal information is posted on the platforms' website. Base on that information, the lenders perform their own screening and provide funding to selected loan requests. If the borrowers did not manage to raise enough money within a certain time, the loan request will be canceled. If the borrowers attracted enough lenders to reach the targeted

[18] See https://www.bloomberg.com/news/articles/2019-01-02/china-s-online-lending-crackdown-may-see-70-of-businesses-close.

funding amount, the loan is funded and at this stage the P2P platform's focus becomes ensuring the borrowers pay back the loan on time. Lenders can choose to wait for borrowers' regular payments, or sell their bonds to other investors. If the borrowers fail to pay off all the money on the due date, a third party might be involved to help recover the lender's loss. To attract lenders, many platforms even offer "principal guarantee", in which the platform pay to cover the principal in case of a borrower default.

d. Fee structure of the P2P platforms

As a facilitator in matching borrowers and lenders, China's P2P platforms obtain their revenues through origination fees collected from the matchmaking process. P2P platforms in China are usually registered as consultancy firms and may charge a service fee ranging from 1 to 10% of the principal loan amount. Service fees usually account for a majority of a platform's profit. P2P platforms' fees consist of three parts: fees paid by the lenders, fees paid by the borrowers, and fees charged from the assignment of debts between lenders. Fees paid by the borrowers usually make up 70% of the revenues generated from the lending business. However, only the fees paid by the lenders are transparent; the exact nature of the other two types of fees is unknown to industry outsiders. This portion of fees includes contribution fees, withdrawal fees, VIP fees and management fees (Shen Wei 2015). More than 80% of P2P platforms do not charge contribution fees from lenders.[19]

f. Platform onboarding

Platforms often collect private information (Tang 2019b), carry out due diligence on borrowers offline, and solicit collaterals to reduce borrowers' default risk. Background checking takes time, and adopting and learning about the rules of the new platform are costly to borrowers (Roson, 2005). For example, Figure A1 shows the common loan process in Chinese P2P markets, which takes several steps until the loan is finally issued.

[19] See China's Internet Lending Business Annual Report 2014.

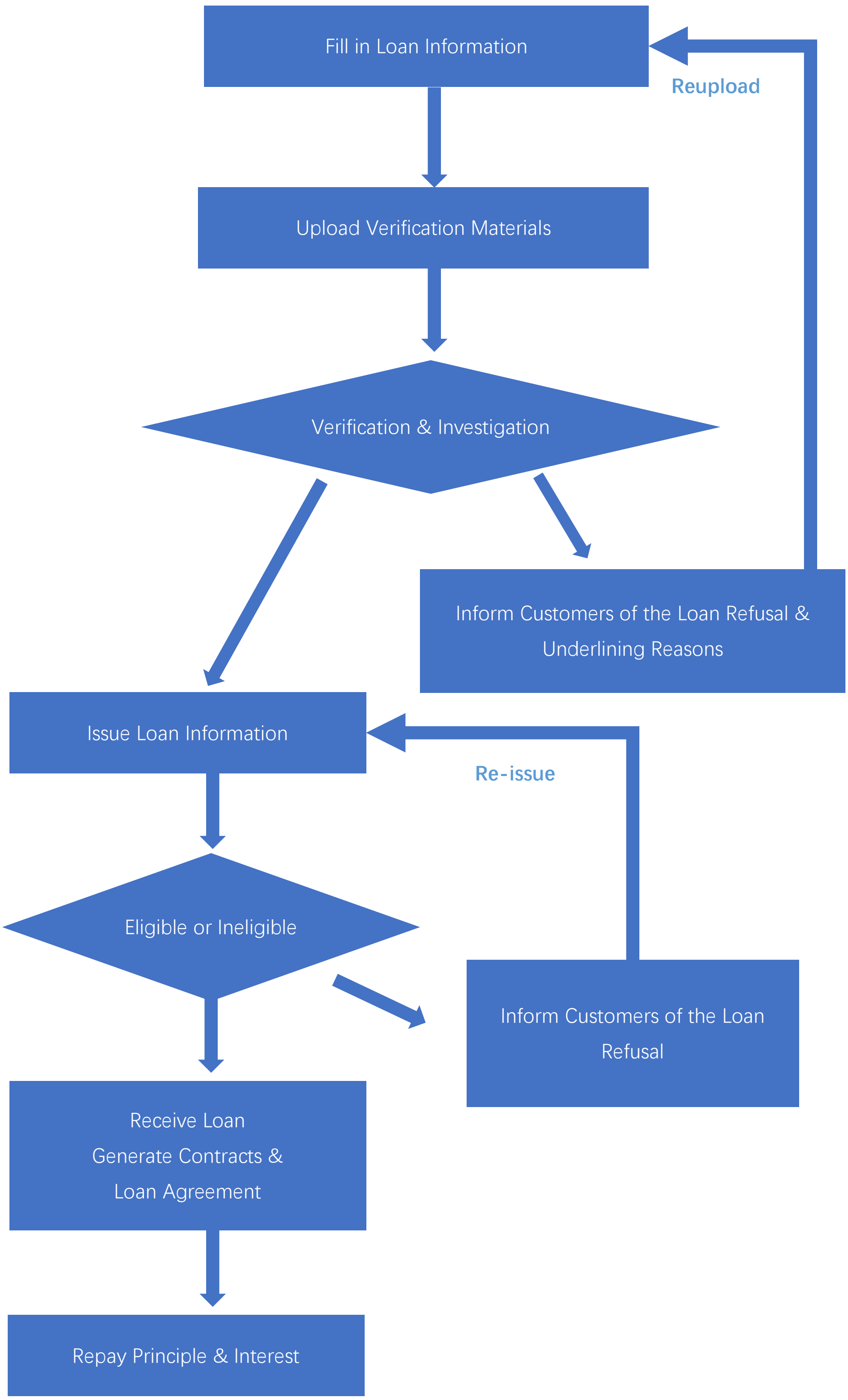

Figure A1. Flow Chart of the Loan Application Process.

g. Platform failures

There are many reasons for which a P2P platform may fail. We list them below, discuss their mechanisms, and provide a concrete illustration. All examples are sampled from our data set.

1. Some P2P platforms, in order to attract lenders and quickly expand the scale of the platform, artificially split the existing borrowing biddings. For example, the platform may split a one-year loan into 12 one-month loans. This caters the lenders' desire for a quick exit. However, the resulting maturity mismatch also means that once the platform fail to find enough new lenders or funding at a certain point in time, it faces face a huge risk of lenders' "run" and an eventual failure.
   Example: Jinrong Express (锦融运通, www.jrexc.com)

2. A second type of platforms neglect the importance of risk management or promise unreasonably high rates of return. They attract low quality borrowers and have a high rate of non-performing loans. The platform becomes unsustainable and closes down.
   Example: Sida Investment (四达投资, www.sidatz.com)

3. Admittedly, the economic slowdown and continued tightening of regulation contributed to the massive failure of Chinese P2P platforms. China began financial deleveraging in 2017 and monetary creation slowed down to the lowest rate in recent history. At the same time, the regulation of shadow banking is further strengthened and standardized, resulting in tighter market credit. The growth rate of AFRE (Aggregate Financing to the Real Economy, stock) dropped to 9.8 percent in December 2018, also a record low. Focusing on P2P online lending itself, regulators have issued a series of documents since 2016; by August

2017, the three major compliance policies for banks in the online lending industry, including depositing, filing and information disclosure, had been implemented according to the 2018 P2P online lending yearbook from www.wdzj.com. Many platforms that work with other financial institutions or are more exposed to aggregate liquidity/ regulatory conditions closed their businesses voluntarily.[20]

Example: GuangZhouDai (广州贷, www.dai020.com)

4. A small fraction of platforms raise fund themselves. That is to say, the owners of the platform directly manage the lenders' money. Once the lender investors rush to withdraw cash or borrowers become delinquent, the platforms' capital chain breaks down, resulting in the final collapse.

   Example: Kings Lend (金喜财富, www.kingslend.com)

5. Some P2P platforms outright frauds. The platform owners take the money and run away after fundraising or when lenders find out the nature of the platforms.

   Example: Zhonghui Online (中汇在线, www.zhonghuizaixian.com)

It should be noted that in many cases, the above causes are overlapping. It is often a combination of several factors that lead to the ultimate collapse of the platform. Other than frauds, all the factors for failure are consistent with our empirical findings: *the acquisition of borrowers once we have lenders is the key to P2P platform survival*. To be more specific, the first type of platforms pays too much attention on the acquisition of lenders and ignores the importance of borrowers, who are more sticky. The second type of platforms, due to the limitation of its own ability of risk management, also fail to ensure the quality of borrowers entering the platform. Factors 3 and 4 also add to these issues. The two case studies next provide more details for the failure mechanism for the majority of platforms.

[20] Some are forced to change their business abruptly. For example, 红岭创投, www.my089.com, switched from large-scale loan business to micro-scale loan business immediately after the regulation policy was implemented and announced that it will close within three years.

Case One: Jinrong Express (www.jrexc.com)

Jinrong Express is a typical platform splitting the borrowing biddings. Jinrong Express has 15 days, 1 month, 2 months, 3 months, 4 months, 5 months and 6 months maturity loan program. The annual yield is the same, but the longer the bidding period, the higher the bidding reward. The platform's average comprehensive annual interest rate is over 20%, so the platform gives the lenders a perception that the interest rate is high and the term is short, which are extremely attractive. From the website, we could find out that Jinrong Express platform often issues multiple loan bids with different terms, which belong to the same loan project. Therefore, it can be inferred that the platform has a high-risk behavior of splitting the biddings. In addition, the number of main borrowers of the platform is as few as 20, while the top four borrowers are all bidding for over 30 million yuan.

On July 29, 2014, a group in Shanghai borrowed 10 million yuan from Jinrong Express, which should be repaid on August 12 of that year. On August 12, the group only paid back 5 million yuan on time, but still owed 5 million yuan. The overdue payment of 5 million yuan directly caused the first withdrawal difficulty of Jinrong Express platform on August 12, when the withdrawal business of the platform was over 7 million yuan. As a reaction, Jinrong issued high-yielding biddings to attract lenders and raise capital, temporarily made up for the withdrawals. On August 13, the platform repaid all the overdue loans, guaranteed the operation of the platform and allowed lenders to withdraw cash normally. However, at the same time, the platform's weak risk management ability enabled the platform to have a collection of as much as 300 million yuan. In order to offset the high fund gap of the platform, the operators once again issued the short-term bid with high yield and continued to attract the lenders with high reward.

In the following week, nearly 3 million yuan flew out of the platform every day. In order to reduce capital outflow, the platform took various measures to persuade lenders from withdrawing. However, on August 14, many lenders were convinced that the collateral procedures of the platform's borrowing targets were not complete and thus the investment funds were not safe. As a result, negative news about the platform kept expanding, more and more lenders choose to withdraw cash, and the fund liquidity of the platform is seriously insufficient. At this time, some of the large lenders began to worry about the "bank run" on the platform and hoped to stabilize the public opinion to reduce the further outflow of platform funds.

On August 21, 2014, the second large-scale failure of withdrawal occurred. The official website of Jinrong Express first released a statement on August 22, saying that due to the failure of a few borrowers to payback their debts, the platform could support to withdraw only 5,000 yuan once a day up to 10 days, and there is no guarantee that everyone can receive the payment. The platform also promised to compensate lenders who failed to withdraw cash by 0.5‰ per day. According to the announcement, Dingge Jiang, the legal person of the platform, had discussed with the representative of the lenders and was willing to pledge the equity of the Guomao hotel under his name to the representative of the lenders. However, it was found afterwards that the equity failed to be successfully pledged due to the incomplete legal procedures. On August 24, 2014, the person in charge of Jinrong Express was no longer available, the company's office was empty, and customer service was unresponsive.

Jinrong was once a very dynamic and promising platform. However, the behavior of splitting the borrowing biddings, as well as the weak risk management made it hard to sustainably develop. Jinrong Express has been seized now and the outstanding debt amounts to 212 million yuan.

Case Two: Sida Investment (www.sidatz.com)

Funded in Yibin and grown in Chengdu, Sida has a transaction volume of over 1.7 billion yuan and is the fourth largest P2P platform in Sichuan province. According to the company’s official website, the amount of investment waiting to be paid back in Sida now reached 231 million yuan, with an average interest rate of 17.83%. There were 5,051 people waiting to receive payback, and the average amount of the payback was 58,000 yuan.

On June 8, 2016, Sida Investment, which has been in operation for four years, began to face cash withdrawal difficulties. In a statement later that afternoon, Sida announced: “Due to the impact of the environment of P2P industry, Sida Investment has been facing difficulties to fill the bid in time recently, which has affected the capital chain.” At the same time, the management of Sida offered to discuss a solution with its lenders.
What have to admit is that Sida's management, unlike those of its fraud-ridden platforms, did not run maliciously during the crisis. Fraud was not the cause of the collapse. Founded by private financiers, Sida has had bad debts since its inception. At that time, Sida’s target was mainly enterprise credit loans. After nine months of operation, the total transaction amount reached 30 million yuan, and the bad debt rate was as high as 60%. Due to the high bad debts, other Sida shareholders started to withdraw their shares and Sida eventually became the sole proprietorship platform of Jian He.

In the second half of 2013, Sida Investment began to transform its target on car loans and gradually reduced bad debts. In this process, Sida Investment started to develop new products while operating the car loans’ business, among which the pledge of raw materials and rosewood were the tried projects.

However, affected by the macroeconomic environment and the decline in market demand, the price of rosewood furniture continued to fall, even fell to a five-year low.

As a result, the ratio of bad loans of Sida Investment again began to climb and did not shrink until the first half of 2016.

Sida Investment is a typical “grassroots” startup. At the beginning, almost all the staff did not understand Internet finance. However, with the rise of the industry, it had once ranked top 100 in the P2P industry. Jian He, as the sole owner of the platform, established his absolute authority when managing the team. With little awareness of risk management, Sida’s business is gradually shrinking and the risks are accumulating after years’ operation. It is not surprising that the main reason for the withdrawal difficulties of Sida is the high bad debt rate. It is estimated that the platform’s bad debts exceeded 50 million yuan, mainly from property mortgage, raw material and rosewood pledges. The number of these bids accounted for nearly 30 per cent of the total.

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