Working Paper presented at the

Peer-to-Peer Financial Systems 2020 Workshop

April, 2019

Asymmetric Cross-side Network Effects on Digital Platforms: Evidence from Marketplace Lending

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First draft: April 2019; current draft: July 2020.

Abstract

Using data on 988 peer-to-peer (P2P) lending platforms in China, we examine the cross-side network effects (CNEs) throughout platform lifecycle in a dynamic industry characterized by entries, exits, and network externalities. We find that unlike borrowers' symmetric CNEs, lenders' CNEs are smaller during platform declines than during platform growth and are predictive of future transaction volumes. These novel asymmetries reflect borrowers' greater stickiness and distinguishing features of financial platforms: lenders and borrowers face divergent risks, incentives, and contracting frictions. We further show that lenders' CNEs strongly predict since inception the platforms' short- and long-term likelihood of survival. Our empirical findings provide new economic insights and inform practitioners, investors, and regulators, about multi-sided platforms in general.

Keywords: Cross-side Network Effects; P2P Lending; Platforms; FinTech

JEL Classification: G19, G23, L13, L81.

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* We thank Greg Buchak, Lin Peng, Mohamed Shaban, Huan Tang, and seminar and conference participants at the Midwest Finance Association Meeting (Chicago), Workshop on "New Frontier on FinTech Studies" at Tsinghua University and Guanghua International Fintech Symposium at Peking University. Ammon Lam, Ziming Wang, and Weiyi Zhao provided excellent research assistance. An earlier draft of the paper was circulated under the title "Survival Scale: Marketplace Lending and Asymmetric Network Effect." This research was funded in part by the Ewing Marion Kauffman Foundation and by the National Science Foundation of China. The contents of this publication are solely the responsibility of the authors. Cong is at the Cornell University Samuel Curtis Johnson Graduate School of Management; Miao is at the Nielsen Company; Tang and Xie are at the Institute of Economics, School of Social Sciences, Tsinghua University. Send correspondence to Cong (will.cong@cornell.edu) or Tang (ketang@tsinghua.edu.cn).

1. Introduction

Two-sided markets are prevalent in a vast array of industries encompassing 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 digital platforms have become one of the most actively researched areas in business economics over the past decades, studies typically focus on pricing and rely on one or two growing platforms, leaving out systematic patterns in the cross-section of the industry and about the dynamics of platforms.[1] Despite recent studies on lending marketplaces and frequent media discussions of fraudulent activities and macroeconomic conditions, little is understood about the distinguishing features of financial platforms and how cross-side network effects (CNEs)---the impact on players on one side of a platform due to the activities of players on the other side--- affect the survival of various online marketplaces.

At the same time, marketplace lending, also known as P2P lending, has experienced phenomenal growth. In its largest market in China, more than 6,000 P2P platforms having been introduced over the past decade (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, triggering sweeping regulatory reforms.

To understand CNEs of two-sided platforms, we utilize a novel data set of 988 Chinese P2P lending platforms. With the elasticity measure for CNE, we

[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.

find that both lenders' CNE and borrowers' CNE are significant and persistent, i.e., increases in lenders' participation lead to subsequent increases in borrows' participation (lender's CNE), and increases in borrower's participation results in subsequent growths in lenders' participation (borrower's CNE). Further analyses reveal the first asymmetry for CNEs: lenders' CNE is about one third smaller in the platform's failing period than that in the take-off period. In contrast, there is no such asymmetry for the borrowers' CNEs.[2]

We attribute the asymmetries to the borrower's stickiness, i.e., their reluctance of leaving, particularly the reduced response to platform failure and lenders' leaving. This phenomenon can be interpreted from three aspects: First, unlike non-financial platforms, marketplace lending entails long-term contracts. Borrowers are on the receiving side and are less concerned with platform failures because they *benefit* if the failed platforms no longer pursue them for paybacks. On the contrary, lenders are on the paying side and worry about both borrowers' credibility and the soundness of the platforms. Second, borrowers still have to provide much information in addition to exerting effort when applying to other platforms (e.g., see Appendix A Figure A1). Because privacy is valuable and effort is not free, switching is costly. To the opposite, lenders face fewer frictions when switching and frequently multi-home to better diversify their risks, both common on financial platforms. 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 peer-to-peer markets, many credit systems for borrowers are proprietary, making it hard for borrowers to multi-home. However, with money being fungible, lenders do not need to build up a reputation on a platform. Overall, as creditors, lenders have incentives and can leave platforms quickly; borrowers face greater frictions or are less incentivized to depart from the declining platform --- they are *stickier* than lenders on P2P platforms.

[2] On the other hand, the borrower's CNEs are rather slightly larger during the failing period relative to the take-off period.

Furthermore, we directly test for borrowers' stickiness using an exogenous scam – the crisis of Ezubao,[3] as well as the failures of more than 400 platforms. We find that the departure rate of borrowers one month after the Ezubao scam is 4% less than that of lenders. Moreover, the number of borrowers leaving the platform is 18% less than that of lenders during the half-year leading to a platform's failure.

Therefore, borrowers' stickiness stabilizes platforms and important for platforms' survival. Hence, lenders' CNEs ---the ability to attract new borrowers with a marginal new lender joining in the platform---are crucial for borrower acquisition. We find that platforms attracting more borrowers with the same increases in lenders tend to grow faster, and the lenders' CNE dominates borrowers' in determining a platform's survival.[4] A one standard deviation increase in lenders' CNEs forecasts a 0.43% reduction in failure probability over the next month. We further show that lenders' CNEs can serve as a robust early predictor of the 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%.

Marketplace lending in China is well-suited for studying two-sided markets. 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 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

[3] Closed on December 2015, Ezubao was once the biggest P2P platform in China, it collected about 60 billion Chinese Yuan from more than 900K investors by illegal Ponzi schemes.

[4] 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 A6, we discuss the various failure mechanisms based on manually investigations of a random sample in our data.

observations that can inform theory and practice. Importantly, we rarely observe large panels of both growing and failing platforms. The unique setting allows us to identify asymmetric network effects systematically for the first time without relying on one or two thriving platforms with idiosyncratic characteristics.

Our findings of asymmetric CNEs have implications for platform owners, and regulatory authorities even in other industries. Platform owners, for example, should aim for effective translation of non-sticky user acquisition to sticky user growth, especially on nascent platforms. For example, online stores on an e-commerce platform are stickier than shoppers.[5] Therefore, attracting those stores becomes crucial for any new E-commerce platform. Regulators can potentially disclose information about CNEs, in order to guide retail investors to better manage risks associated with platform failures.

Our paper contributes 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' multi-homing (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 cross-side network effects and their roles in platform evolution --- a little understood area as Chu and Manchanda (2016) point out. We are the first to consider platform failures and to relate asymmetric CNEs to the specialty of financial platforms.

Empirically, a large literature measure CNEs in VCRs (Ohashi, 2003), video

[5] As the online shops normally have its reputation on a certain platform, it is quite hard for them to switch to other platforms, opposite to the shoppers.

games (Shankar and Bayus, 2003), personal digital assistants and software (Nair et al. 2004), etc.[6] 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 growing platforms 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, Iyer, Khwaja, Luttmer, and Shue (2015) and Jagtiani and Lemieux (2017) show how alternative data enable Prosper and LendingClub to enhance lending efficiency and outperform traditional lending respectively; Hildebrand, Puri, and Rocholl identify adverse incentives in P2P lending and discuss how they shape crowdfunding structure and regulation; 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

[6] 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).

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 industrial organization. Most also use data from the United States and Europe, except for Jiang, Liao, Wang, and Zhang (2018) which studies whether government affiliation is a valid signal about platform quality in China. We complement by focusing on asymmetric CNEs in the largest market for P2P lending and the mechanisms extend beyond the Chinese crowdfunding market. We also analyze how various platform attributes affect network effects and platform scale, providing new insights on the C2C business model on digital platforms.

More broadly, our paper relates to FinTech and crowdfunding (both reward-based and equity-based) platforms.[7] 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 cross-side network effects 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 remainder of the paper is organized as follows. Section 2 describes our data. Section 3 measures the CNEs empirically and shows their asymmetry. Section 4 presents the predictability on platform failures using CNEs, discusses

[7] 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.

their implications for practitioners and regulators, and highlights distinguishing features of financial platforms as compared to non-financial platforms. Section 5 concludes.

2. Data Description

We mainly use two data sets, both from Zero One Finance, a private data vendor specializing in P2P lending data. The first data set covers transactions on 1,404 P2P platforms at a weekly frequency from June 26, 2007, to June 30, 2018.[8]

We delete platforms deemed fraudulent by Chinese courts, because our paper focuses on general economic mechanisms, not frauds or Ponzi schemes. We also 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.[9]

Our data contain the 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 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. As shown in Figure 1, the survival rate (estimated from the Kaplan and Meier methodology) keeps going down, staying around 40% after 4 years.

[8] 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. Note that after June 2018, the Chinese government has a crackdown on P2P lending platforms (Wu, Peng, and Han, 2018). As we study the CNEs from a market perspective, we exclude the sample after June 2018.
[9] 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 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), the average number of loans per borrower/lender, the average investment size per lender and the 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 4 ($\exp(5.777 - 4.455)$) times that of failed platforms, while the number of loans for live platforms is about three times relative to that of failed ones. The loan and investment sizes are both larger (56% and 20% more) for live platforms than failed ones. 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, the borrowing amount per borrower is 60% more for live platforms relative to defunct ones, and the investing 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 data set 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 investment 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.

In addition, 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. Asymmetric Cross-side Network Effects

When a new user enters one side of a P2P platform, users on the other side face more choices and hence higher chances of finding a transaction counterparty. For example, the more lenders participate, the larger is the market potential for borrowers to achieve funding goals; when more borrowers participate, they in turn attract more lenders with more investment opportunities and potential diversification. Therefore, boosting CNEs constitutes an integral task for platform owners to grow the platform.

3.1 Measuring Network Effects

We follow Stremersch et al. (2007) and Chu et al. (2016) to measure the *elasticity* of the number of new loans initiated by borrowers in period t+1 to the number of active lenders in period t, and then call that the lenders' CNE at time t+1. Similarly, we use the elasticity of the number of new investments by the lenders in period t+1 to the number of active borrowers in period t as the borrowers' CNE at time t+1.

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 investment opportunity 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 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 (or the same-side network effect) on the same side.

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

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

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

where $N_{i,t}^{Inv}$ is the number of investments that lenders make on a platform *i* at week *t*; $N_{i,t}^{Loan}$ is the number of loans listed 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). Note that 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,[12] thus it is likely that borrowers raise funds at a monthly frequency. Moreover, since most people receive salaries on a monthly basis, it is also likely that retail lenders invest at such frequencies. b_1 is the borrowers' CNE, and c_1 is the lenders' CNE, both calculated over a rolling window of 52 weeks. $I_{i,t}$, $lnLS_{i,t}$ and $lnIA_{i,t}$ are interest rates, log loan size and log investing amount in the t^{th} week on the i^{th} platform, respectively.

[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 investing amounts per lender are *all* missing, we use investment per loan instead, given that they are highly correlated.
[12] This can be found on the loan purpose of lending club (https://www.lendingclub.com).

Panel A of Table 2 reports both borrowers' and lenders' CNEs for the lifespan of all platforms. The average of CNEs for borrowers and lenders are 0.257 and 0.229, respectively. About 80% platforms have a positive borrower's or lender's CNEs, respectively. Panel B of Table 2 documents the borrowers' and lenders' CNEs for the first year of all platforms, which show a similar pattern with the quantity of Panel A. Table 4 shows both borrowers' and lenders' CNEs during the failing period (one year before platforms fail). The average borrowers' and lenders' CNEs are both significantly positive. 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 answers the "chicken-and-egg" paradox in the P2P platforms, i.e. both the chicken (borrower) and the egg (lender) are important. In Appendix B, we also analyze the social-economic factors that influence the CNEs.[13]

Turning to the same-side network effect of platforms, Table 2 shows that the average serial correlations for lenders' and borrowers' numbers are 0.333 and 0.294, respectively. The evidence suggests positive same-side network effects for both the borrowers and lenders. 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

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[13] Panel A of Appendix B 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. 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.

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.

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 lender's CNE. Even though we document same-side network effects, we follow the literature on two-sided markets to focus on CNEs (Armstrong 2006; Rochet and Tirole 2003, 2006 et al.) because the goal of P2P platform is to facilitate trades between the two sides (borrowers and lenders).

Figure 2 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 those of the failed ones during the first two years after birth. As mentioned before, platforms with larger CNEs tend to have a higher growth rate in the expansion period than those with smaller CNEs. In a competing market, platforms with large CNEs tend to outperform their peers in terms of platform scale, and hence have better performances (see Section 4.1). It is thus rational for entrepreneurs to work hard to boost the CNEs in the platform's infancy. In contrast, failed platforms have a lower and 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, in Section 4.3, we will present the predictability of early-stage CNEs on the failure of the platforms.

Second, 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.

Figure 3 shows that the average borrower's and lender's CNEs trend down along time. This is likely due to gradually increased competition caused by increased number of platforms, as shown in the Herfindahl concentration index of the P2P industry in China, which decreased significantly after 2011, indicating a gradually amplified competition in the P2P industry in China. Less concentration in the P2P industry diversifies borrowers and lenders across different platforms, therefore reduce the network effects.

3.2 Asymmetric CNEs in the Platform Lifecycle

As the CNE is the elasticity of one-side player on the number of trades on the other side by definition, it can be different when the platform experiences 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 number of users leave the platform. Moreover, during failing periods, borrowers and lenders have different stickiness to the platforms, which leads to asymmetric borrower's and lender's CNEs; while this asymmetry does not exist in the platform take-off periods. Consistent with this phenomenon, in Table 3, we group the CNEs according to the lifecycle of failed platforms into three categories: one year after the starting date (P1), the middle year[14] (P2) and one year prior to failure (P3). We then calculate the average borrowers' and lenders' CNEs in the three periods.

For borrowers' CNEs, the difference between the starting and failing periods is quite small and statistically insignificant (as shown in the t-statistics). This finding is also consistent with the first plot of Figure 2, where the borrowers' CNEs for the failed platforms exhibit 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. Overall, the difference in borrower's and lender's CNE differences in a take-off or failing platform is prominent with a magnitude of -0.08 and t-statistics of -2.3.

This informs an *asymmetric* lender's CNEs, i.e. it is much smaller in the failure period than that in the take-off period. As the lender's CNE refers to the

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

borrowers' participation with the arrival or departure of a marginal lender, the asymmetric lender's CNEs, thus, inform that borrowers like to enter the platform in the fast-growth period, but have less incentive to leave the platform in a failing period. This is consistent with the notion that borrowers do not usually have incentives to leave the platform even in the failing period. This also explains why in the second plot of Figure 2 we do not see a clear increase beyond 2.5 years of a platform's age.

As a placebo test, we also check the same-side (direct) network effect (SNE) in the lifecycle of the platforms. We take the b_2 and c_2 in equation (1) and (2) as the measure of the lender's and borrower's SNEs, respectively. Appendix B.2 shows that both lender's and borrower's SNEs slightly increase in the failing period compared to the birth period, which is opposite to the prominent decrease of lender's CNEs (or the asymmetric lender's CNEs). The increase of borrower's SNE is lower than that of lender's SNE, with the difference-in-difference effect of -0.024 and t-statistics of -1.1.

3.3 CNEs and Status of Platforms

Similar with the lifecycle analysis of the platforms, this section utilizes the entry or leave of users as the proxy for the status of a platform (growth or decline), and analysize the CNEs associated with the status of a platform[15]:

$$CNE_{i,t}^{Player} = b_0 + b_1 Negative(\Delta lnCN_{i,t}^{Player}) + b_2 I_{i,t} + b_3 lnLS_{i,t} + b_4 lnIA_{i,t} + u_{i,t+1} \quad (3)$$

where *player* is either lender or borrower, $CNE_{i,t}^{Player}$ 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. $\Delta lnCN_{i,t}^{Player} = lnCN_{i,t}^{Player} - lnCN_{i,t-12}^{Player}$ is the change of player's number from t to t-12. $Negative(x)$ is 1 when x is negative and zeros otherwise. Control variables are $I_{i,t}$, $lnLS_{i,t}$ and $lnIA_{i,t}$ representing

[15] Note that through this regression we aim to analyze the correlation (but not causality) between the CNEs and platform status.

interest rates, log loan size and log investing amount in the t^{th} week on the i^{th} platform, respectively. t denotes the lifetime of a platform with a monthly frequency, ranging from 1 to 4 years.

We conduct a Fama-MacBeth regression with the Newey-West method to adjust standard errors. The first two columns in Table 4 show that the borrower's CNE is slightly lower but insignificant (also in a small magnitude) when borrowers leave the platform (decline period) relative to that when borrowers enter the platform (growth period). This informs that the movement of lenders responds to the arrivals and departures of borrowers in a roughly symmetric way.

In contrast, the third and fourth columns in Table 4 show that the lender's CNE is much lower with a great significance (t-statistics more than 5) when lenders leave the platform relative to that when lenders enter. The magnitude, -0.12, is economically quite large given the lender's CNE in growth period is only about 0.22 (the constant in column 3), a 54% drop!

Since in the Fama-Macbeth regression, we have the time series of estimated coefficients on $Negative(\Delta lnCN_{i,t}^{Player})$ for both borrower's and lender's CNEs at each month, we, therefore, can obtain the difference in borrower's and lender's CNE differences in a growth or decline platform, which is quite significant with a magnitude of 0.09 (0.12-0.03) and t-statistics of 10.9. This significant difference-in-difference effect emphasizes the different reluctance-of-leaving of borrowers and lenders, which will be illustrated in more detail in Section 3.4.

As a placebo test, we also run the same regression for the same-side network effect, SNE, for both borrowers and lenders. Table B.3 shows that the SNEs are slightly smaller for both borrowers and lenders in declining periods than in growing period, but the magnitude is much smaller relative to the decrease of lender's CNE in declining periods. Furthermore, the difference of the borrower's and lender's SNE difference is almost zero.

Overall, Section 3.2 and 3.3 show that the lender's CNE is asymmetric, much lower compared with lender's CNE in the growing period and borrower's CNE in the declining periods. This phenomena do not exist for the borrower's and lender's SNEs.

3.4 Explanation of the Asymmetric CNEs

We interpret the asymmetry of borrower's and lender's CNEs discussed in Section 3.2 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 platforms, i.e. they normally do not face large contractual friction. Diversification of platform risks also drives them to multi-home. This explains why borrowers' CNEs have a quite small difference in growth and decline periods, 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 borrowers leave the platform, lenders are also free to leave, which also causes a large borrowers' CNE.

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 an underdeveloped credit reference system for individuals and small enterprises. 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. Appendix A5 lists the specific procedure of this screening process. 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.

Moreover, borrowers are on the receiving side and are less concerned with platform failures, they actually benefit if the platform no longer pursues them for paybacks. On the contrary, lenders are the paying side and thus are more concerned about the platform failures, when the platform will not monitor the borrowers to pay.

These frictions could shed light on the asymmetry of take-off and declining periods 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. Such frictions of borrowers generate "stickiness," defined as the incentive to lengthen staying duration or reluctance of leaving a platform, 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.

3.5 Direct Tests on Asymmetric Stickiness

As mentioned before, asymmetric CNEs come from the different stickiness, or the reluctance of leaving, of borrowers and lenders during a platform's stress periods. In this subsection, we perform direct tests on the stickiness based on two shocks: the Ezubao fraud, and the platform failures.

Ezubao fraud. Ezubao, once the biggest P2P platform in China, was shut down on December 8, 2015, due to the illegal Ponzi scheme that collected about 60 billion Chinese Yuan from more than 900K investors.[16] The Ezubao scam was a shock to the Chinese P2P industry. Many borrowers and lenders contemplate leaving P2P platforms after realizing they could be victims of similar scams. We use the Ezubao incident as an external shock to examine borrowers and lenders' stickiness.

Specifically, we choose a 16-week (4 months) window centered around the

[16] Refer to https://www.reuters.com/article/us-china-fraud-idUSKCN1BN0J6

Ezubao closure date and use a difference-in-differences specification to study the stickiness of borrowers and lenders:

$$lnN_{i,t}^{player} = b_0 + b_1 dummy1 + b_2 dummy2 + b_3 dummy1 \times dummy2 + b_4 I_{i,t} + b_5 lnLS_{i,t} + b_6 lnIA_{i,t} + \theta_i + u_{i,t}, \quad (4)$$

where $N_{i,t}^{player}$ is the active number of borrowers or lenders at the t^{th} week of platform i. $dummy1$ is an indicator for the event that equals one in the weeks after December 8, 2015, and zero otherwise and $dummy2$ is a dummy variable that equals one for borrowers and zero for lenders; θ_i is the platform fixed effect dummy. The coefficient on the diff-in-diff effect, b_3, therefore presents the difference in the leaving rates between borrowers and lenders.

Table 5 shows a positive coefficient of the diff-in-diff item with a 5% significance level. Specifically, it shows that facing the Ezubao scam, the staying population for borrowers is 4% more than that of lenders on average. This is consistent with the notion that the borrowers are stickier to the platform relative to the lenders.

Large-sample analysis of departures preceding platform failures. Next examine the departure rate of the borrowers and the lenders 6 months before a platform failure. Borrowers and lenders tend to leave the platforms with the expectation of the platform failure, but they might have different eagerness to leave. Panel A of Table 6 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 a platform's failure, we then take the difference to its previous month.

Panel A of Table 6 shows that borrowers have a smaller leaving rate than those of lenders for every month before the platform failure. On average, the monthly difference of log number changes between borrowers and lenders is 3% with a t-statistics around 3.5, which corresponds to an 18% population difference in the half-year before failure. This observation, again, informs that borrowers are more reluctant to leave, or stickier to the platform than the lenders before the platform failure.

As a placebo test, in Panel B of Table 6, we also report the change of log numbers of borrowers and lenders up to 6 months after the platforms' birth. We cannot find a consistent pattern that borrowers enter faster or slower than the lenders, and the overall entering rate difference between borrowers and lenders is small and insignificant.

Overall, in this section, through two different types of shocks (Ezubao and platform failures), we show that borrowers are more reluctant to leave relative to lenders. This is consistent with the notion that borrowers have a stronger stickiness than lenders, and therefore, prefer to stay at the platform for a longer time.

4 Implications of Asymmetric CNEs and Financial Platforms

As mentioned in Sections 3.2 and 3.3, since lenders' CNEs are different in periods of growth and decline, it should have predictive power on platform failure. That said, a large lenders' CNE is likely to go together with a fast platform growth period and hence a low likelihood of failure, and a small lender's CNE signals either a bad platform performance (slow platform growth) or stress and shrinking platforms close to failure. Given that the status of platforms tends to continue for a certain period, lenders' CNEs, thus, have predictability on the platform scales. On the contrary, borrowers' CNEs do not have these predictions because of free entry and departure by lenders.

4.1 CNEs and Platform Scale Dynamics

We now formally analyze the predictability of CNEs on the growth of the platforms, or the change of platform scale (proxied by transaction volumes).[17] We firstly perform a Fama-MacBeth regression with a monthly frequency:

$$\Delta lnV_{i,t+1} = b_0 + b_1 CNE_{i,t}^{B} + b_2 CNE_{i,t}^{L} + b_3 lnV_{i,t} + controls + CalendarYearDummy + u_{i,1}, \quad (5)$$

where $\Delta lnV_{i,t+1}$ is the change of log transaction volume at the *t+1* month of the i^{th} platform. $CNE_{i,t}^{L}$ and $CNE_{i,t}^{B}$ denotes the lenders' and borrowers' CNEs, respectively, calculated with a one-year rolling window.[18]

Panel A of Table 7 shows that lenders' CNE has a positive and significant influence on the platform trading volume 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 positive impact on the future trading volumes. 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 and insignificant. Therefore, only the lenders' CNE can predict platform growth consistently. A larger lenders' CNE implies positive growth of platform scales, one standard deviation increase in lenders' CNEs forecasts a 1.12% increase in the platform scale the next month (more than 13% on an annual basis). This finding echoes the result of the previous section: borrowers are sticky, but lenders are not. Using a different way of lining up platforms as a robustness check, Panel B is consistent with the result in Panel A of Table 7.

Next, we answer the question: why are platform scales so important? We show that platform scale (proxied by transaction volume) is essential to make platforms achieving better efficiency and risk diversification.[19] Particularly, if

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[17] Note that, trading volumes for exchanges or platforms are normally regarded as a proxy for the scale of them. For example, many third-party companies rank exchanges by trading volume, e.g. https://coinmarketcap.com/rankings/exchanges/.

[18] Note that in this section, we use monthly frequency mainly because platform failures happen every month. Using a frequency higher than monthly would invalidate regression (5) because some periods would not have any failure at all.

[19]Section 4.2 also shows that the platform scale is a good predictor for the platform failure.

projects on platforms are heterogeneous, it is relatively easier for the lenders to find their favorite projects and therefore have a better matching efficiency. Moreover, 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.

We, therefore, take the origination time of achieving the full amount of a loan as a proxy for matching efficiency, and the percentage of top 10 investments and loans as the measure of concentration (the opposite measure of risk diversification) for both lenders and borrowers, respectively, and run the following Fama-Macbeth regressions:

$$lnM_{i,t+1} = d_0 + d_1 lnV_{i,t} + d_2 I_{i,t} + d_3 lnLS_{i,t} + d_4 lnIA_{i,t} + CalendarYearDummy + u_{i,t+1} \quad (6)$$

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 or the percentage of top 10 investments (loans) in 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 (36 months). Panel A of Table 8 shows a significantly better matching efficiency in large platforms than that in small ones: A 1% increase in the platform scale reduces the average origination time by 0.9%. Moreover, Panel B documents that both investment and loan concentration decrease as platforms become larger, which means platforms with larger scales achieve a better risk diversification. A 1% increase in platform scale decreases both the investment and loan concentration by around 0.1%.

Overall, lenders' CNEs show asymmetric values for scenarios of platform growth and decline respectively; whereas borrowers' CNEs instead have symmetric values more or less.

4.2 CNEs and Platform Failures

We run a predictive Fama-MacBeth regression for the failure of platforms:

$$F_{i,t+1} = c_1 CNE_{i,t}^{L} + c_2 CNE_{i,t}^{B} + c_3 lnV_{i,t} + controls + CalendarYearDummy + u_{i,t+1} \quad (7)$$

Panel A of Table 9 demonstrates that the lenders' CNEs can strongly predict the platform's failure in both OLS and Logit regressions, respectively. A larger lenders' CNE implies a lower rate of platform failure. For example, one standard deviation increase in lenders' CNE leads to a 0.43% decrease in failure probability next month (5% on an annual basis). This is consistent with Section 3.2 and 3.3 in that distressed platform normally exhibit lower lenders' CNEs than growing platforms: lenders' CNEs are important in forecasting the survival of P2P platforms due to the first asymmetry in lenders' CNEs during platforms' rises and declines.

As in Panel B, we also perform robustness checks with an alternative line-up of platforms. The asymmetric impact of lenders' CNE on the platform failure still holds: larger lenders' CNEs result in a reduction of a platform's future failure rate significantly at the 1% level.

4.3 Early Prediction of the Platform Failure

As mentioned before, survival platforms normally have the ability to attract borrowers in the take-off period because borrowers are stabilizers of platforms. Lender's CNEs are a good proxy for the ability to attract borrowers given a certain number of lenders. Therefore, in this section, we directly test the link between the early-period lender's CNEs and destiny (failure or survival) of platforms. Specifically, we examine how the CNE calculated by the first year of a platform launch affects the default rate in its future life:

$$F_{i,1} = b_0 + b_1 CNE_{i,0}^{B} + b_2 CNE_{i,0}^{L} + b_3 lnV_{i,0} + b_4 I_{i,0} + b_5 lnLS_{i,0} + b_6 lnIA_{i,0} + u_{i,1}, \quad (8)$$

where $CNE_{i,0}^{L}$ and $CNE_{i,0}^{B}$ are the lenders' and borrowers' CNEs calculated for the first year of the i[th] 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 investing 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 until the end of sample 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 (9). In particular, we assume the hazard rate $h_{i,1}$ of the i[th] platform after the first year is as follows:

$$h_{i,1} = b_0 + b_1 CNE_{i,0}^L + b_2 CNE_{i,0}^B + b_3 lnV_{i,0} + b_4 I_{i,0} + b_5 lnLS_{i,0} + b_6 lnIA_{i,0} + u_{i,1} \quad (9)$$

Table 10 reports the results. It is somewhat surprising that lenders' CNE in the first year has such a 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 life. From the OLS regression, one standard deviation increase in lenders' CNEs reduces 7.3% of the probability of platform failure. This is consistent with previous findings in Section 3 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. In contrast, borrowers' CNEs do not have such a predictive capability. Turning to control variables, one standard deviation increase of trading volume tends to decrease the probability of failure by 12.9%, as larger platforms will have smaller future failure rates. High interest rates, as a reflection of low loan quality, also foretell a higher failure rate in the future.

Note that lenders' asymmetric CNEs imply that 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. The degree of asymmetry within the lenders' CNE would eventually affect the survival of a platform in the future.

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 after birth can provide 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. In the meanwhile, 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 on a P2P platform when it is initially launched also likely raises its future probability of failure.

4.4 Distinguishing Features of Financial Platforms

It is worth noting that the asymmetries in CNEs can be attributed to the distinguishing features of financial platforms. Unlike non-financial platforms that involve transactions completed in a short span of time (e.g., the purchase of a book on Amazon, or short-term rentals on AirBnB), financial platforms often entail the transfer of money across time. Agents on one side of the platform face default risks originating from both agents on the other side of the platform and the platform itself. This means financiers have to multi-home and diversify and are more likely to leave a platform when transaction counterparties decrease. The borrowers or receivers of financing, on the other hand, face different risk profiles and would not easily leave a platform even when the transaction counterparties decrease. Such unique features caused borrowers' stickiness and the patterns we document.

4.5 Business and Regulatory Implications

As mentioned before, borrowers are more important than lenders for P2P platforms due to their stronger stickiness. 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 (sticky side) 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.[20]

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 CNEs can, therefore, assist regulators. For example, regulators can closely monitor platforms' CNEs to anticipate platform failures. They can also disclose platform statistics such as trading volumes, interest rates 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.[21]

5. Conclusion

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

[21] Even in developed countries, crowdfunding platforms attract mostly retail investors (see Baeck, Collins, and Zhang, 2014).

Motivated by the rapid growth of FinTech marketplace lending across the globe and its massive entries and failures in China, we study the cross-side network effects (CNEs) of the marketplace lending platforms since the main purpose of these platforms is to facilitate the trading between both sides (i.e. borrowers and lenders). Specifically, we measure the cross-side network effects using the elasticity of participation from one side on the number of users from the other side, and empirically show that borrower's CNEs are symmetrically positive in both fast-growing and failing periods of platforms, which is caused by lenders' easy entry and easy 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. These asymmetries reflect unique features of financial platforms and inherent differences between lenders and borrowers' objectives and risks, and frictions of switching platforms arising from contract incompleteness and agency issues. Because of this asymmetry, the lender's CNEs can predict the future failure of P2P platforms, even at a very early stage. Our findings not only inform the theory on two-sided platforms, but also provide guidance for platform owners, retail investors, and regulators.

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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 from June 26, 2007, to June 30, 2018. In Panel A, we compute the average life-span 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	NA	2.2

Panel B: Various Features on P2P Platforms

	Mean(all)	Std(all)	Mean (live)	Std(live)	Mean(failed)	Std(failed)
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 (seconds, 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. Measuring Cross-side Network Effects

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

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

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

where $N_{i,t}^{Inv}$ and $N_{i,t}^{Loan}$ are the number of investments and loans at the tth 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 tth week on the ith platform, respectively. b_1 stands for the borrowers' CNE, and c_1 stands for the lenders' CNE, both calculated by a rolling one-year window. Panel A and B show the statistics of the CNE of the whole lifespan and of the first year, respectively. The correlations between borrowers' and lenders' CNEs are 0.47 and 0.54, respectively, in the whole lifespan and in the first year.

Panel A: CNEs in the Platforms' Whole Life

	Borrowers' CNE, b_1	Lenders' CNE, c_1	Lenders' Serial Corr, b_2	Borrowers' Serial Corr, c_2
Average	0.257	0.229	0.333	0.294
Std Dev	0.356	0.309	0.293	0.279
Max	1.345	2.274	1.601	1.405
Min	-0.939	-0.591	-0.599	-0.285
Positive (%)	78.0%	79.5%	88.3%	86.5%
Negative (%)	22.0%	20.5%	11.7%	13.5%
Positive with 95% significance (%)	34.7%	35.5%	53.4%	47.7%
Negative with 95% significance (%)	2.6%	0.5%	0.3%	0.5%
Non-significance (%)	62.7%	64.0%	46.4%	51.8%

Panel B: CNEs in the First Year

	Borrowers' CNE, $\boldsymbol{b_1}$	Lenders' CNE, $\boldsymbol{c_1}$	Lenders' Serial Corr, $\boldsymbol{b_2}$	Borrowers' Serial Corr, $\boldsymbol{c_2}$
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 3. Cross-side Network Effects in the Platform's Lifecycle

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' CNE	0.153	0.136	0.172	0.018
	[0.029]	[0.030]	[0.035]	[0.042]
Lenders' CNE	0.172	0.154	0.110	-0.062
	[0.022]	[0.027]	[0.028]	[0.031]
Diff (Lender-Borrower)	0.018	0.018	-0.062	-0.080
	[0.025]	[0.029]	[0.031]	[0.035]

Table 4. Asymmetry of Cross-side Network Effects

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

$$CNE_{i,t}^{Player} = b_0 + b_1 Negative\left(\Delta lnCN_{i,t}^{Player}\right) + controls + u_{i,t+1}$$

where *player* is either lender or borrower, $CNE_{i,t}^{Player}$ 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). $\Delta lnCN_{i,t}^{Player} = lnCN_{i,t}^{Player} - lnCN_{i,t-12}^{Player}$ is the change of the player's cumulative number from t-12 to t. $Negative(x)$ 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.

	$CNE_{i,t}^{B}$		$CNE_{i,t}^{L}$	
$Negative\left(\Delta lnCN_{i,t}^{Borrower}\right)$	-0.033	-0.029		
	(-1.339)	(-1.281)		
$Negative\left(\Delta lnCN_{i,t}^{lender}\right)$			-0.116	-0.119
			(-5.664)	(-5.544)
$I_{i,t}$		-0.366		-0.101
		(-1.577)		(-0.762)
$lnLS_{i,t}$		-0.008		-0.015
		(-1.974)		(-1.321)
$lnIA_{i,t}$		-0.015		0.007
		(-7.179)		(1.687)
Const	0.150	0.241	0.218	0.276
	(6.285)	(4.096)	(15.066)	(4.445)
R^2	0.5%	1.7%	2.0%	2.9%

Table 5. Participation of Players before and after the Ezubao Crisis

We choose a 16-week (8 weeks before and 8 weeks after) window centered on the Ezubao closure date, December 8 2015, for 668 live platforms during this period. We perform the following difference-in-differences regression:

$$lnN_{i,t}^{player} = b_0 + b_1 dummy1 + b_2 dummy2 + b_3 dummy1 \times dummy2 + b_4 I_{i,t} + b_5 lnLS_{i,t} + b_6 lnIA_{i,t} + \theta_i + u_{i,t},$$

where $N_{i,t}^{player}$ is the active number of borrowers or lenders at the t^{th} week of platform *i*; *dummy1* is an indicator for the event that equals one in the weeks after December 8, 2015 and zero otherwise and *dummy2* is a dummy variable that equals one for borrowers and zero for lenders; θ_i is the platform fixed effect dummy. $I_{i,t}$, $lnLS_{i,t}$ and $lnIA_{i,t}$ are interest rates, log loan size and log investing amount within the t^{th} week on the i^{th} platform, respectively. Quantities in brackets are the t-statistics.

dummy1	-0.054	-0.038
	(-2.721)	(-2.063)
dummy2	-2.483	-2.482
	(-53.556)	(-53.374)
dummy1*dummy2	0.041	0.036
	(2.264)	(1.950)
$\boldsymbol{I_{i,t}}$		3.426
		(2.405)
$\boldsymbol{lnLS_{i,t}}$		0.209
		(6.434)
$\boldsymbol{lnIA_{i,t}}$		-0.199
		(-6.361)
Platform fixed effect	Yes	Yes
R^2	73.8%	74.3%

Table 6. Leaving Users Before Platform Failures

Panel A of 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 the platform's failure, we then take the difference to its previous month. Panel B follows the same procedure of Panel A, but for months after the birth of the same platforms. Quantities in square brackets are standard deviations.

Panel A: Before Platform Failures

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

Panel B: After Platform's Birth

Months after Birth	Average Log Number Changes for Borrowers	Average Log Number Changes for Lenders	Difference (Borrower - Lender)
1	0.008	0.010	-0.002
			[0.019]
2	0.045	0.020	0.026
			[0.020]
3	0.017	0.024	-0.007
			[0.023]
4	0.095	0.065	0.030
			[0.025]
5	0.078	0.110	-0.031
			[0.027]
6	0.039	-0.007	0.046
			[0.034]
Average	0.047	0.037	0.010
			[0.010]

Table 7. CNEs and Platform Growth

Table 7 reports the predictability of borrower's and lender's CNEs on the change of platform scales (proxied by trading volumes) via the Fama-MacBeth regression:

$$\Delta lnV_{i,t+1} = b_0 + b_1 CNE^B_{i,t} + b_2 CNE^L_{i,t} + b_3 lnV_{i,t} + Controls + TimeDummy + u_{i,1}$$

$V_{i,t+1}$ is the trading volume at the t+1 month for the i[th] platform. $CNE^L_{i,t}$ and $CNE^B_{i,t}$ are the lenders' and borrowers' CNEs, respectively, calculated with a one-year rolling window. In Panel A, t is indexed by the life time of a platform with a monthly frequency, ranged from 1 to 4 years (36 months). $TimeDummy$ is the calendar year dummy grouped as $[\leq 2012, 2013, 2014, 2015, 2016, \geq 2017]$. In Panel B, t is indexed by calendar time in a monthly frequency from January 2015 to June 2018 (42 months). $TimeDummy$ is thus an age dummy grouped as $[1, 2, 3, 4, 5, > 5]$. At each month 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 36 and 42 lags for Panel A and B, respectively. Quantities in brackets are the t-statistics.

Panel A: Platforms Lined up by Life Time

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

Panel B: Platforms Lined up by Calendar Time

	(1)	(2)	(3)
$NE^B_{i,t}$	0.010		0.000
	(1.067)		(0.015)
$NE^L_{i,t}$		0.024	0.024
		(2.291)	(2.935)
$lnV_{i,t}$	-0.017	-0.018	-0.018
	(-4.097)	(-4.191)	(-4.460)
Controls	Yes	Yes	Yes
Age Dummies	Yes	Yes	Yes
R^2	4.7%	4.7%	5.0%

Table 8 Platform Scales, Matching Efficiency and Risk Diversification

This table reports the benefit of large platform scales via matching efficiency and risk diversification by running the following two Fama-Macbeth regressions:

$$lnM_{i,t+1} = d_0 + d_1 lnV_{i,t} + d_2 I_{i,t} + d_3 lnLS_{i,t} + d_4 lnIA_{i,t} + CalendarYearDummy + u_{i,t+1}$$

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 month (in Panel A) or the percentage of top 10 investment in the i[th] platform at the t+1[th] month of its lifetime (in Panel B). t is indexed by the lifetime of a platform with a monthly frequency, from 1 to 4 years (36 months). 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: Platform Scales and Matching Efficiency

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

Panel B: Platform Scales and Risk Diversification

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

Table 9. CNEs and Platform Failure

Table 7 reports the predictability of borrower's and lender's CNEs on platform scale (proxied by trading volumes) via the Fama-MacBeth regression:

$$lnF_{i,t+1} = c_0 + c_1 CNE^L_{i,t} + c_2 CNE^B_{i,t} + c_3 lnV_{i,t} + Controls + TimeDummy + u_{i,t+1}$$

$F_{i,t+1}$ is a dummy variable that equals one when the i[th] platform fails at month t+1, and 0 otherwise. $CNE^L_{i,t}$ and $CNE^B_{i,t}$ are the lenders' and borrowers' CNEs, respectively, calculated with a one-year rolling window. In Panel A, t is indexed by the life time of a platform with a monthly frequency, ranged from 1 to 4 years (36 months). $TimeDummy$ is the calendar year dummy. In Panel B, t is indexed by calendar time in a monthly frequency from January 2015 to June 2018 (42 months). $TimeDummy$ is thus an age dummy that is grouped as $[1, 2, 3, 4, 5, > 5]$. At each month 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 36 and 42 lags for Panel A and B, respectively. Quantities in brackets are the t-statistics.

Panel A: Platforms Lined up by Life Time

Specification	OLS			Logit		
$NE^B_{i,t}$	-0.002		0.002	-0.089		0.089
	(-1.194)		(0.937)	(-1.823)		(1.124)
$NE^L_{i,t}$		-0.009	-0.011		-0.323	-0.389
		(-9.288)	(-7.001)		(-6.586)	(-4.734)
$lnV_{i,t}$	-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
R^2	3.2%	3.2%	3.4%	3.7%	3.7%	4.0%

Panel B: Platforms Lined up by Calendar Time

	OLS			Logit		
$NE^B_{i,t}$	0.002		0.007	-0.057		0.196
	(1.329)		5.121	(-0.906)		(3.828)
$NE^L_{i,t}$		-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
R^2	3.9%	4.0%	4.2%	4.9%	5.0%	5.2%

Table 10. Early-stage CNEs and P2P Platform Failure

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

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

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 until the end of our sample and 0 otherwise. We use both the OLS and logit regressions to estimate our regressions.

We also analyze the lifespan 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:

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

Quantities in brackets are the t-statistics.

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

Figures

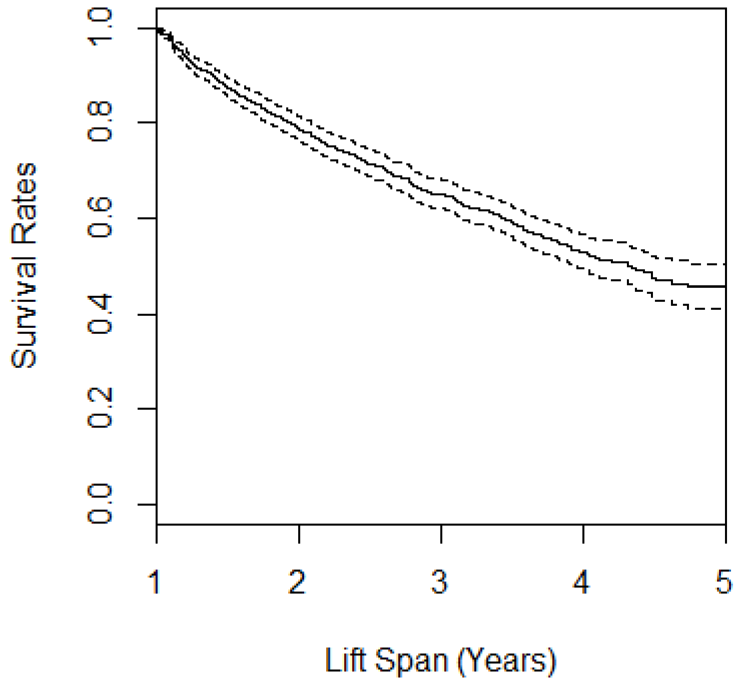

Figure 1 Kaplan-Meier Survival Rate vs. Platform Lifespan

The dotted line shows the 95% confidence levels.

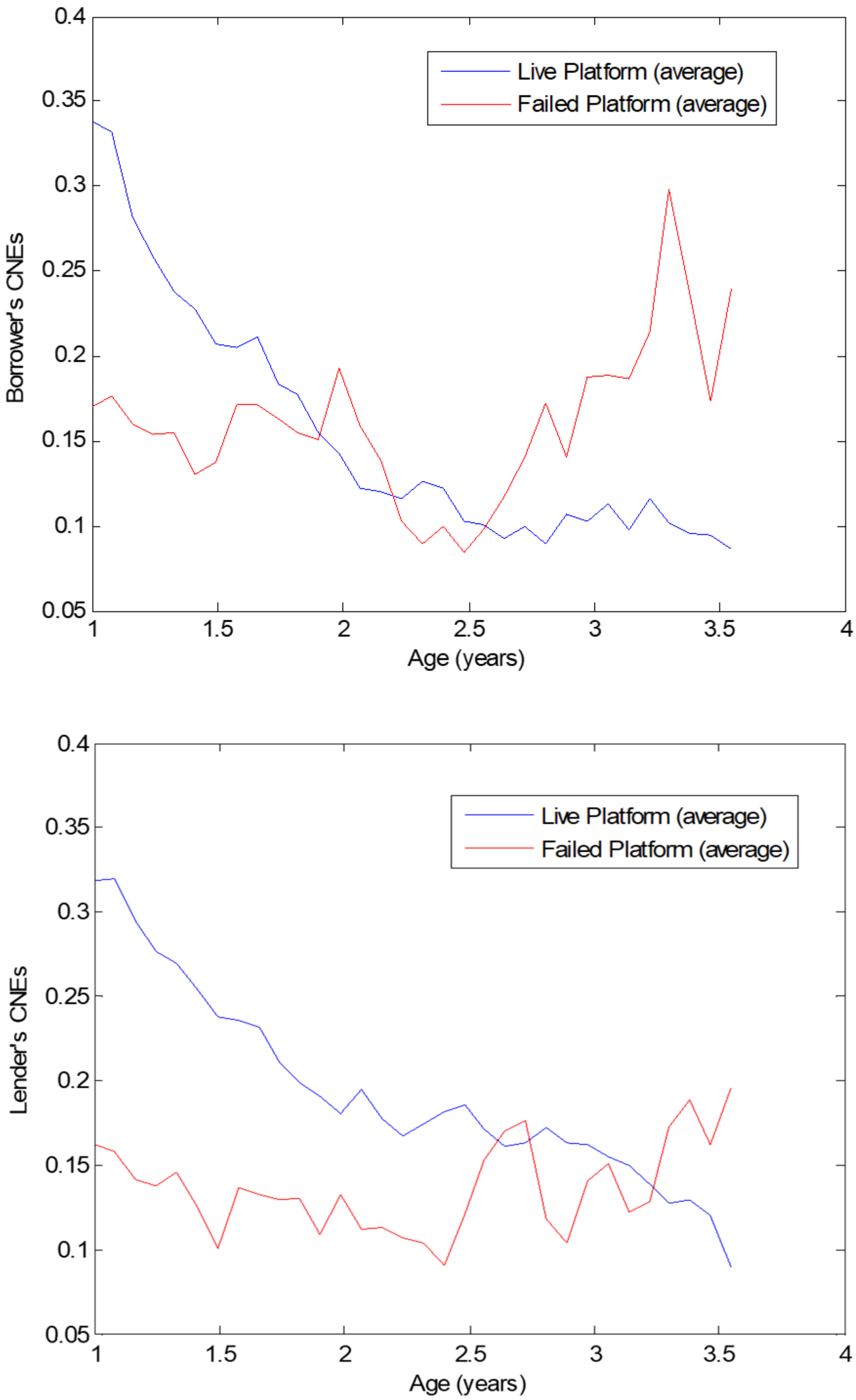

Figure 2. Network effects for borrowers and investors.

The borrowers' and lenders' CNEs are obtained by regressions with a one-year rolling window. This figure shows average CNEs for live and failed platforms, respectively.

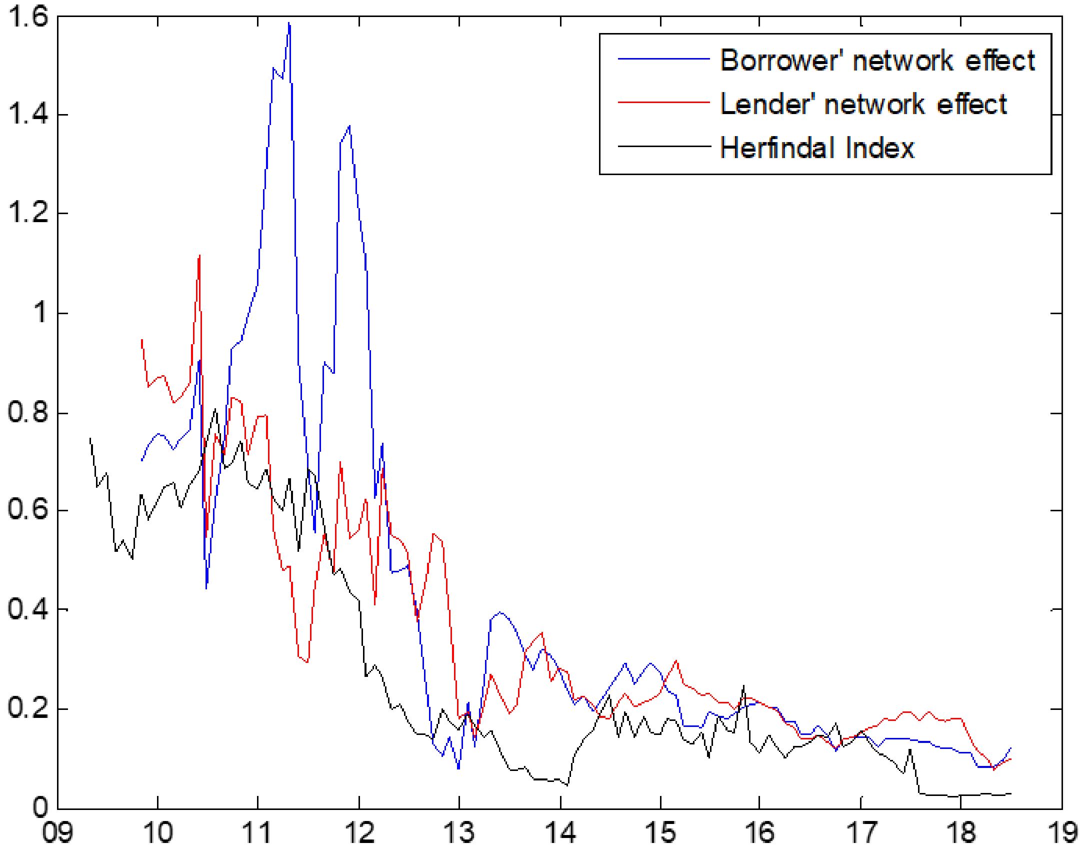

Figure 3. Borrower's and Lender's CNE and Herfindahl Concentration Index for the Chinese P2P Lending Markets.

Appendix A. Institutional details on P2P lending

A1. A brief history of p2p lending

Peer-to-peer lending (P2P lending) is the practice of directly matching lenders and borrowers through online services. The P2P platforms do not lend their own funds but act as facilitators to both the borrowers and lenders. 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.[22] 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.[23]

A2. 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. In China, more than 6,000 P2P platforms having been introduced over the past decade (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).

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

[22] See www.lendingclub.com.
[23] See https://www.bloomberg.com/quicktake/peer-peer-lending.

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).

Tightening regulation and cracking down of platforms that fail to meet the standard were executed after June 2018. The number of platforms dropped by more than 50 percent to 1,021 at the end of 2018 due to failing to comply with the regulations.[24] 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 individuals and small enterprises, a large supply of funds from retail investors, and market failure in the provision of credit.

A3. Mechanics of China's P2P lending platform

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. 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 do not

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

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 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 debts to other investors. If borrowers fail to pay off all the money on the due date, sometimes, a third party (the insurance company) might be involved to help recover the lender's loss.

A4. 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.

A5. 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.

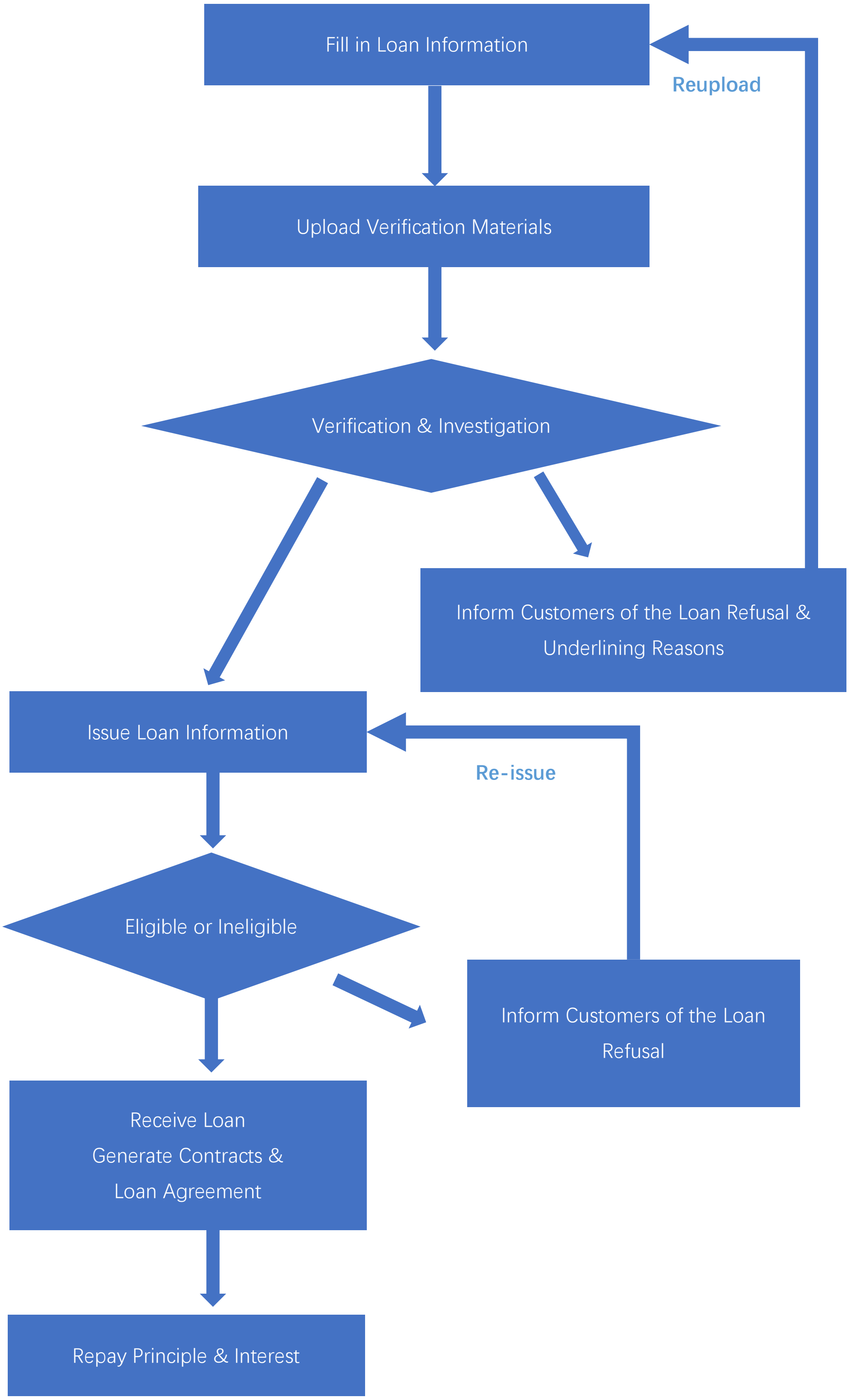

Figure A1. Flow Chart of the Loan Application Process.

A6. 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 fails to find enough new lenders or funding at a certain point in time, it faces a huge risk of lenders' "run" and eventual failure.

   Example: Jinrong Express (锦融运通, www.jrexc.com)

2. The second type of platforms neglects 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. The economic slowdown 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.

   Example: GuangZhouDai (广州贷, www.dai020.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 to the acquisition of lenders and ignores the importance of borrowers. The second type of platforms, due to the limitation of its own ability of risk management, also fails to ensure the quality of borrowers entering the platform. Factors 3 also add to these issues. The two case studies next provide more details for the failure mechanism for the majority of platforms.

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 is 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. 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. 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.

On August 21, 2014, the second large-scale 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 pay back their debts, there is no guarantee that everyone can receive the payment. 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 afterward 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.

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."

Founded by private financiers, Sida has had bad debts since its inception. 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. Many borrowers cannot repay their debts. 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. In 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, 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 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.

Appendix B. Appendix Tables

B.1 Determinants of CNEs

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

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

where $CNE_i^{B,L}$ is the borrowers' (CNE_i^B) or lenders' (CNE_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 CNEs

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

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

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

Table B.2. Same-side Network Effects (SNE) in the Platform's Lifecycle

In this table, we group the SNEs 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' SNEs 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' SNE	0.209	0.212	0.241	0.032
	[0.018]	[0.019]	[0.020]	[0.023]
Lenders' SNE	0.233	0.252	0.288	0.056
	[0.019]	[0.018]	[0.020]	[0.023]
Diff(Lender-Borrower)	-0.024	-0.039	-0.047	-0.023
	[0.015]	[0.017]	[0.017]	[0.020]

Table B.3. Same-side Network Effects (SNE) and Platform Status

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

$$SNE_{i,t}^{Player} = b_0 + b_1 Negative\left(\Delta lnCN_{i,t}^{Player}\right) + controls + u_{i,t+1}$$

where *player* is either lender or borrower, $SNE_{i,t}^{Player}$ is the player's (lender's or borrower's) SNEs at the t^{th} month of the i^{th} platform lifetime, calculated with a rolling one-year window (from t-12 to t). $\Delta lnCN_{i,t}^{Player} = lnCN_{i,t}^{Player} - lnCN_{i,t-12}^{Player}$ is the change of the player's cumulative number from t-12 to t. $Negative(x)$ 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.

	$SNE_{i,t}^{B}$		$SNE_{i,t}^{L}$	
$Negative\left(\Delta lnCN_{i,t}^{Borrower}\right)$	-0.029	-0.024		
	(-2.159)	(-1.578)		
$Negative\left(\Delta lnCN_{i,t}^{lender}\right)$			-0.024	-0.024
			(-3.754)	(-3.015)
$I_{i,t}$		-0.535		-0.060
		(-13.761)		(-0.634)
$lnLS_{i,t}$		-0.014		-0.010
		(-2.293)		(-7.557)
$lnIA_{i,t}$		-0.042		-0.033
		(-6.280)		(-8.538)
Const	0.232	0.374	0.255	0.326
	(156.7)	(26.12)	(69.20)	(24.16)
R^2	0.4%	3.1%	0.4%	2.6%

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