Asymmetric Cross-side Network Effects on Financial Platforms：Theory and Evidence from Marketplace Lending*

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Abstract

Using data on 988 peer-to-peer lending platforms in China, we examine the cross-side network effects (CNEs) throughout platforms' lifecycle in a dynamic industry characterized by entries, exits, and network externalities. We find that unlike borrowers' symmetric CNEs, lenders' CNEs are smaller on declining and smaller platforms than on growing, new, or larger platforms. Borrowers' CNEs are also larger than lenders' CNEs, especially for declining or sub-scale platforms. We rationalize the asymmetries in a model of two-sided platforms with endogenous failures and empirically motivated distinguishing features of financial platforms---lenders' portfolio diversification, differential impacts on agents of platform failures, and borrowers' stickiness due to contracting frictions. The model further predicts that lenders' CNEs predict the platforms' scale and survival likelihood, among others, which the data corroborate. Our findings provide novel economic insights on multi-sided platforms and inform FinTech practitioners and regulators.

Keywords: Network Externality; P2P Lending; Platforms; FinTech

JEL Classification: G19, G23, L13, L81.

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** Miao primarily contributed to an initial manuscript by the same authors that focused on empirically predicting platform failures using cross-side network effects (nested in the current paper).

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 and Amazon. 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 the dynamics of platforms especially when failure probability is non-trivial due to fierce competitions. Despite recent studies on lending marketplaces and crowdfunding sites, or 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 and scale of various online marketplaces.

To understand CNEs on multi-sided platforms, we first document in a novel data set of 988 Chinese P2P lending platforms that both lenders' and borrowers' CNEs are significant and persistent. We empirically demonstrate for the first time two asymmetries in CNEs: (i) lenders' CNE is bigger for platforms that are new, growing, or large in scale than lenders' CNE for platforms that are terminal, declining, or small in scale; (ii) borrowers' CNEs are no smaller than lenders' CNEs on average, and the gap between the borrowers' and lenders' CNE is wider for struggling, declining, or small platforms. To rationalize our findings, we innovate on classical models of multi-sided platforms (e.g., Armstrong, 2006; Rochet and Tirole, 2003, 2006) by modeling platform failures and highlighting distinguishing elements of financial platforms such as risk diversification and realistic frictions in joining and leaving platforms. The model generates not only CNE asymmetries, but also rich predictions and implications further corroborated in the data. In particular, lenders' CNEs predict platform survival (extensive margin) and scale (intensive margin); platform scale also predicts future platform survival (interaction of intensive and extensive margins).

We draw empirical evidence from marketplace lending, also known as P2P lending, as a representative of financial platforms. It is also an important and interesting market to study, having experienced phenomenal growth globally. Marketplace lending in China is especially well-suited for studying two-sided markets. First, FinTech has the biggest impact in emerging economies where traditional financial sectors fail to meet rising demands and internet-based marketplace lending potentially enhances financial inclusion by serving the unbanked, discriminated, and disadvantaged. Second, in China, more than 6,000 P2P platforms having been introduced over the past decade (2018 P2P online lending yearbook, www.wdzj.com), with more than two-thirds have failed or were under serious stress by the end of 2018.[1] For the first time, FinTech platforms constitute such a significant fraction of the economy and their massive failures indisputably raise concerns about financial stability and systemic risks, triggering sweeping regulatory reforms. Third, from a research perspective, we rarely observe large panels of both growing and falling 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.

Specifically, we find persistent and robust patterns that increase in lenders' participation leads to subsequent increases in borrows' loan issuance (positive lenders' CNE) and increases in borrower's participation results in subsequent growth in lenders' investment (positive borrowers' CNE). Lenders' CNE is about one-third smaller on failing, shrinking platforms than on upcoming and growing platforms while such an asymmetry is absent for borrowers' CNE. We also find that the gap between borrowers' and lenders' CNE is more pronounced on small, failing, or shrinking platforms.

Obviously, CNEs partially come from better search and matching, which we empirically verify. But we attribute the asymmetries mostly to distinguishing features of financial platforms. Unlike non-financial platforms that feature mostly spot transactions, financial platforms entail long-term contracts and time transformation of

[1] 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). For some background knowledge, please refer to Appendix A.

money. Borrowers are on the receiving side and are less concerned with platform failures because they *benefit* when failed platforms no longer pursue them for paybacks; lenders are on the paying side and worry about not only diversification of borrowers' delinquency risks but also the losses from platform failure. Furthermore, incumbent borrowers typically build reputation or social connections on current platforms (Burtch et al., 2014). Without a well-established credit rating or reference system in peer-to-peer markets, credit systems for borrowers are typically proprietary, making it hard for them to leave. However, with money being fungible, lenders do not need to build up a reputation on a platform.

We empirically verify that lenders do enjoy greater diversification with a larger number of borrowers on the same platform and that borrowers are *stickier* than lenders on P2P platforms.[2] We then incorporate these distinguishing features of financial platforms into an otherwise canonical model of two-sided platforms. We show they indeed lead to a gap of borrowers' and lenders' CNEs. We also derive that borrowers' stickiness indeed causes a small elasticity to the departure of lenders, and hence causes a low lenders' CNE under adverse market sentiments (such as when the platform is small, failing, or shrinking). The asymmetries further reveal that lenders' CNE is predictive of unobservable sentiment towards financial platforms. In other words, lenders' CNE forecasts a platform's failure rate (extensive margin). The model also predicts that CNEs help forecast platform scale (intensive margin) and that platform scale predict platform failure going forward (interaction between the intensive and extensive margins).

We test the predictions in the data and find corroborating evidence. For example, a larger lenders' CNE predicts a 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). A one standard deviation increase in

[2] To direct test the stickness of the borrowers, we first examine the borrowers' stickiness using an exogenous scam and collapse of Ezubao, apparently once China's largest P2P lending platform that collected about 60 billion RMB from more than 900K investors through Ponzi schemes, 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.

lenders' CNEs forecasts a 0.43% reduction in failure probability over the next month. Note that a platform fails when there is no more transaction, normally due to players on one side all left the platform.[3] We further show that lenders' CNEs and platform scale can serve as robust early predictors of platforms' lifespan and failure rates in the long run. In particular, one standard deviation increase in the first-year lenders' CNE decreases the probability of platform failure by 7.3%.

Our findings, especially asymmetric CNEs, borrower stickiness, and scale, augment our fundamental understanding of multi-sided platforms and of financial platforms, with potential implications for platform owners, participants, and regulators. Platform owners, for example, should aim for effective translation of non-sticky user acquisition to sticky user growth, especially on nascent platforms. Regulators can potentially disclose information about CNEs to guide retail investors in managing risks associated with platform failures.

Our paper contributes to studies on network externalities in two-sided markets. Rochet and Tirole (2003) highlight in their seminar study the prevalence of two-sided markets and the importance of price allocation, subsequent studies derive price dependence externality size and multi-homing (Armstrong, 2006), price structure to "get both sides on board" (e.g., Rochet and Tirole, 2006), CNEs' exacerbation of platform competition (Clements and Ohashi, 2005), and the impact of platform compatibility on sales and consumer welfare in particular industries (e.g., Lee, 2013). 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 model platform failures and distinguishing features of financial platforms and to empirically corroborate the theoretical predictions.

Empirically, a large literature measures CNEs in VCRs (Ohashi, 2003), video games (Shankar and Bayus, 2003), personal digital assistants and software (Nair et al. 2004),

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

etc.[4] Our measurement follows closely the approach in the literature such as Chu et al. (2016) that computes the CNE as the increase in the number of new buyers (sellers) per percentage increase in sellers' (buyers') installed base, and Stremersch et al. (2007) that uses the elasticity of hardware sales to lagged software availability and that of software availability to the lagged hardware installed base as CNE measures. To our best knowledge, we are the first to measure CNEs on 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 the relationship with banks and the quality of screening. Using data from either Prosper.com or LendingClub, Lin, Prabhala, and Viswanathan (2013), Iyer, Khwaja, Luttmer, and Shue (2015), Jagtiani and Lemieux (2017), and Allen, Peng, and Shan (2019) show how alternative data such as online friendship or aggregate social connection inform credit quality, enhance lending efficiency, and help outperform traditional lenders; Hildebrand, Puri, and Rocholl identify adverse incentives in P2P lending that shape crowdfunding structure and regulation; Roure, Pelizzon, and Thakor (2019) 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 substitutes banks in serving infra-marginal borrowers yet complements banks regarding small loans. None of the studies examines multiple lending platforms and most use data from the United States and Europe, except for Jiang, Liao, Wang, and Zhang (2019) which studies whether government affiliation is a valid signal about platform quality in China. We contribute by highlighting asymmetric CNEs' presence on financial platforms,

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

both theoretically and using data from the largest market for P2P lending and crowdfunding in recent years.

More broadly, our paper relates to FinTech and crowdfunding (both reward-based and equity-based) platforms.[5] Also studying network effects in crowdfunding is Bellefamme, Lambert, and Schwienbacher (2019) that uses data from two competing reward-based crowdfunding platforms in France to analyze the interplay of social learning, network effects, and platforms' performance. The authors focus on same-side network effects, which complements our study. The cross-project learning channel they identify also helps microfound our economic channels. We add by identifying unique features concerning financial platforms and providing evidence of their impact on platform dynamics and the industrial revolution.

The remainder of the paper is organized as follows. Section 2 describes our data. Section 3 measures CNEs on P2P lending platforms and documents their asymmetries. Section 4 discusses the distinguishing features of financial platforms with empirical evidence. Section 5 introduces a model of financial platforms to rationalize the asymmetries and provide further predictions and implications. Section 6 corroborates model predictions in the data, including the predictability of platform failures using CNEs, then discusses their practical and regulatory implications. Section 7 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.[6]

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

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

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.[7]

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 have kept increasing. 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.

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

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

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 borrowers' loans on a subset of platforms. The percentage of the top 10 largest loans averaged along each month is reported at a monthly frequency. We have 402 platforms with loan concentration data. Panel B of Table 1 shows that the loan concentrations are 57.6% vs. 81.6% 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

In this section, we first measure the cross-side network effect (CNE) for different platforms and then analyze the asymmetry of CNEs for lenders and borrowers, respectively.

3.1 Measurement of CNEs

We follow the empirical literature on two-sided platforms (e.g., Stremersch et al., 2007 and Chu et al., 2016) to define lenders' CNE at time t+1 as the *elasticity* of the number of new loans initiated by borrowers at time t+1 to the number of active lenders at time t. Similarly, borrowers' CNE at time t+1 is the elasticity of the number of new investments by lenders at time t+1 to the number of active borrowers in period t.

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.[8] 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.[9] We run a weekly time-series regression over an annual window 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,[10] thus it is likely that borrowers raise funds at a monthly frequency. Moreover, since most people receive salaries monthly, 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 (one year). $I_{i,t}$, $lnLS_{i,t}$ and $lnIA_{i,t}$ are interest rates, log loan size and log investing amount per lender in the t^{th} week on the i^{th} platform, respectively.

[8] 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.
[9] 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.
[10] This can be found on the loan purpose of lending club (https://www.lendingclub.com).

Table 2 reports both borrowers' and lenders' CNEs for the live and failed platforms, respectively. The average CNEs of borrowers and lenders are 0.257 and 0.229, respectively, for failed platforms and 0.302 and 0.33 for live platforms. About 80% of platforms have positive borrower's or lenders' CNEs, and the average borrowers' and lenders' CNEs are significantly positive for both failed and live platforms. Both borrowers' and lenders' CNEs are persistent, the autocorrelations (with an annual sampling interval) are 0.18 (t-statistics 14.6) and 0.20 (t-statistics 17.9), respectively. In Appendix B, we also analyze the social-economic factors that influence CNEs.[11]

3.1.1 Asymmetric Lenders' CNEs based on Platform Status

We find that lenders' CNEs depend on the expected status of a platform such as its lifecycle stage, scale, and trends. Not that this expected status is not always observable ex ante and may be only imperfectly predicted. For example, while whether a platform is at its inception is observable, whether it is close to its demise (final lifecycle stage) is uncertain. Similarly, whether a platform is going to be big tomorrow is stochastic but may be imperfectly predicted from today's scale if platform scale exhibits persistence.

3.1.2 Platform Lifecycle Stages

As the CNE is the elasticity of the number of trades on the one side to the number of opposite-side agents 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 lenders' 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

[11] 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 (2019) 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.

platforms into three categories: one year after the starting date (P1), the middle year[12] (P2) and one year before 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. In contrast, the lenders' CNEs are more than 1/3 lower in the failing year relative to their starting year. Overall, the difference-in-difference effect in the borrower's and lenders' CNEs for the take-off and failing periods is prominent with a magnitude of -0.08 (t-statistics of -2.3).

This informs an *asymmetric* lenders' CNEs, i.e. it is much smaller in the failure period than that in the take-off period. As the lenders' CNE refers to the borrowers' participation with the arrival or departure of a marginal lender, the asymmetric lenders' CNEs, thus, inform that borrowers like to enter the platform in the fast-growth period, but have less incentive to leave in a failing period, i.e. the borrowers have stronger stickiness to stay on the platform.

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 lenders' and borrowers' SNEs, respectively. Appendix B.2 shows that both lenders' and borrowers' SNEs slightly increase in the failing period compared to the birth period, which is opposite to the prominent decrease of lenders' CNEs (or the asymmetric lenders' CNEs). The increase of borrowers' SNE is lower than that of lenders' SNE; the difference-in-difference effect is -0.024 with the t-statistics of -1.1.

3.1.3 Platform Scales and Trends

Similar to the lifecycle analysis of the platforms, this section utilizes platform scale and its trends (the entry or departure of players over the trailing 12 months) as proxies for the status of a platform (growing vs. declining, large vs. small) and analyzes its relationship to the platform CNEs.[13] Since the major source of revenue is proportional

[12] Middle year is chosen as a half year before the middle point of a platform's life to a half year after.
[13] The reason to choose one year is that the loan issuing and the personal incomes normally have seasonalities.

to the trading volume, we, therefore, take the trading volume as the proxy for the scale of a platform, and run the following panel regression:

$$CNE_{i,t}^{Player} = b_1 Negative(\Delta V_{i,t}) + b_2 ln\ V_{i,t} + controls + YearFixedEffect + FixedEffect + u_{i,t+1} \quad (3)$$

where *player* is either lender or borrower, $CNE_{i,t}^{Player}$ is the player's (lenders' or borrower's) CNEs of the i^{th} platform at the t^{th} month measured with a rolling window of one year. $\Delta V_{i,t}$ is the change of the trading volume over the past year, indicating trends. $Negative(x)$ is a dummy variable, which is 1 when x is negative and zeros otherwise. Control variables are $I_{i,t}$, $lnLS_{i,t}$ and $lnIA_{i,t}$ representing interest rates, log loan size and log investing amount in the t^{th} month on the i^{th} platform, respectively.

We find that lenders' CNEs increase with the scale of platforms, both economically and statistically significantly. They are also higher when platform scales trend up over the past year. One standard deviation increase of (log) trading volume tends to increase the lenders' CNEs by 1.7%. However, platform scale and growth have positive but insignificant effects on borrowers' CNEs. Results in Table 4 remain robust when using player's numbers instead of trading volume as proxies for platform scale. We find that the borrowers' CNE is not lower with statistical significance when borrowers leave than when they enter. But the lenders' CNE is significantly lower (a 20% decrease) when lenders leave when they join the platform---an asymmetry of CNEs. We leave out the detailed presentation for brevity.

These are consistent with the notion that the lenders' CNE is smaller during the failing period, whereas the borrowers' CNE is rather symmetric in the initial and final stages of a platform's lifecycle.[14] Table B.3 in Appendix B finds similar results when estimating the results with a Fama-Macbeth regression.

Overall, lenders' CNE is asymmetric, being much lower during platform declines or for small scales or when a platform is close to failing, than during platform growth or for large scales or during platform inception. Borrowers' CNEs, in contrast, do not

[14] Results in Table 4 remain robust when using player's numbers instead of trading volume as proxies for platform scale, although we leave out the detailed presentation for brevity.

depend significantly on the status of platforms. In other words, lenders' CNEs are more sensitive to the platform's lifecycle stage, scale, and recent trend, relative to borrowers' CNEs.

3.2 Asymmetric CNEs between Lenders and Borrowers

We also find a second asymmetry in that borrowers' CNEs are in general larger than lenders, after controlling for agents' characteristics. The asymmetry is larger for declining or small platforms, or platforms in its final stage of the lifecycle.

3.2.1 CNE Spread and Platform Status (Scale)

From Table 3, we have already observed that borrowers' and lenders' CNEs are not statistically different through much of platforms' lifecycle until platforms enter their final stage (close to failing) in which borrowers' CNEs are larger. In other words, the CNE spread is larger for platforms in the final stage of lifecycle (failing).

Since the lenders' CNE is small during the platform failing period (corresponding to a small platform scale) relative to the growing period, but borrowers' CNE does not have this effect; the spread of borrowers' CNE over the lenders' CNEs should be large for a small platform. Therefore, there should be a negative relationship between the CNE gap and the platform scale. We hence run the following panel regression:

$$CNE_{i,t}^{Borrower} - CNE_{i,t}^{Lender} = b_0 + b_1 Negative\left(\Delta V_{i,t}\right) + b_2 lnV_{i,t} + controls + u_{i,t+1} \tag{4}$$

The control variables are interest rates, log loan size and log investing amount per lender, respectively.

Table 5 shows that the CNE gap does decrease in the platform scale: A one standard deviation drop of platform scale tends to increase the CNE gap by 0.02. Moreover, the CNE gap is increased by 0.014 when the platform declines than when it grows. This is consistent with the notion that lenders' CNE is smaller in the declining or smaller platforms. We also note that the constant in the regression is significant and positive, which indicates that borrowers' CNE is larger than lenders' CNE, other things being equal. The magnitude, 0.124, is big after controlling other variables, given that the average lenders' CNE is 0.28. [15] Note that Appendix B.4 presents consistent results where the regression in (4) is performed with the Fama-Macbeth method (Newey West adjusted errors).

4. Distinguishing Features of Financial Platforms and Drivers for Asymmetric CNEs

4.1 Distinguishing Features of Financial Platforms

Given that CNEs due to improved search and matching efficiencies do not explain the asymmetries, we consider a few distinguishing features of financial platforms. Unlike non-financial platforms that involve transactions completed in a short 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 risks of loan default or project failure originating from both agents on the other side of the platform and the platform itself. This means financiers have to multi-home and diversify their portfolios. The borrowers or receivers of financing, on the other hand, face less risks from platform failure. If anything, they benefit from a platform's failure if they do not have to pay back the loans.

Moreover, lenders can easily leave a platform when transaction counterparties decrease. Borrowers, in contrast, would not easily leave a platform even when the transaction counterparties decrease, because they incur significant effort and costs joining alternative platforms (due to, e.g., screening) and often lose the credit and reputation they build on the current platform (Burtch et al., 2014). This could be quite important in a country like China with an underdeveloped credit reference system for individuals and small enterprises. Data privacy and propriety concerns, combined with the general lack of public rating systems for small borrowers, imply that borrowers face greater contractual frictions that prevent them from easily leaving platforms.

[15] As a robustness check, we use the player's number instead of trading volume to be the proxy of the platform scale, consistent results are obtained as those in Table 5.

Note that this borrowers' "stickiness" --- the tendency to lengthen staying duration or reluctance of leaving a platform --- can be viewed as unique to financial platforms. On non-financial platforms, buyers (the financiers' equivalent), may return items or file false claims about shipping or item quality, and most platforms accommodate such requests by incurring additional costs to the platform or sellers. As such, non-financial platforms often maintain a rating system for the buyers as well as for the sellers, even though buyers' money is fungible while sellers' goods and quality are typically differentiated. 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.

4.1 Persistent CNE, Scale, and Matching Efficiency

Obviously, persistent CNEs are partially driven by the existence of cross-side network externality from more efficient search and matching. We first verify that CNEs through the matching channel exist.

If projects on platforms are heterogeneous, it is relatively easier for the lenders to find their favorite projects when more borrowers come to the platform and issue loans, it, therefore, improves the matching efficiency. On the other hand, if more lenders come to the platform, borrowers are likely beneficial for the potentially easier fulfillment of loans. We take the origination time of funding the full amount of a loan as a proxy for matching efficiency for both lenders and borrowers, respectively. We run the following panel regressions:

$$lnM_{i,t+1} = d_1 lnN_{i,t}^{player} + d_2 I_{i,t} + d_3 lnLS_{i,t} + d_4 lnIA_{i,t} + d_5 lnM_{i,t} + CalendarYearDummy + FixedEffect + u_{i,t+1} \quad (5)$$

where $M_{i,t}$ is the average origination time (in seconds) that a project has achieved its full-scale amount on the i[th] platform at the t month. $N_{i,t}^{player}$ is the number of the player (borrower or lender) at month t in platform i.

Panel A of Table 6 shows a significantly lower loan origination time on larger platforms with more borrowers or lenders than smaller ones: A 1% increase in the borrowers (lenders) tends to reduce the average origination time by 0.13% (0.12%).

This certainly proves that more players on the platform tend to increase the matching efficiency of the platform.

4.3 Lenders' Risk Diversification

We first demonstrate the impact of more borrowers on a platform for lenders' diversification. Diamond (1984) shows that large banks tend to have a portfolio with more loans and hence achieve a better risk diversification. For financial platforms as P2P platforms, a similar notion applies, i.e. lenders tend to be more diversified when more borrowers (loans) are on the platform. Intuitively, more players on a platform will lead to less concentration, we run the following panel regression:

$$CT_{i,t+1} = d_1 lnN_{i,t}^{player} + d_2 I_{i,t} + d_3 lnLS_{i,t} + d_4 lnIA_{i,t} + d_5 CT_{i,t} + CalendarYearDummy + FixedEffect + u_{i,t+1} \quad (6)$$

where $CT_{i,t}$ denotes the percentage of top 10 loans on the i^{th} platform at the t^{th} month, which is a measure of concentration (the opposite to diversification). Panel B of Table 6 documents that loan concentration decreases as players increase, which means platforms with a larger number of players achieve a better loan diversification. A 1% increase in player's number tend to roughly decrease the loan concentration by around 0.1%.

Next, we directly test the borrower's loan concentration on the effect of the lenders' diversification; we directly run the amount per investment for lenders on the concentration of loans through the following panel regression:

$$lnDI_{i,t+1} = d_1 CT_{i,t} + d_2 lnN_{i,t}^{Lender} + d_3 I_{i,t} + d_4 lnLS_{i,t} + d_5 lnIA_{i,t} + d_6 lnDI_{i,t} + YearFixedEffect + PlatformFixedEffect + u_{i,t+1} \quad (7)$$

where $DI_{i,t}$ is the average amount per investment at the t^{th} month on the i^{th} platform. Panel C of Table 6 shows that when loans are 1% more diversified (less concentrated), the average amount per investment shrinks by 0.04%, i.e. lenders are more diversified. This result provides evidence that diversification is another benefit relating to the CNEs, but uniquely for financial platforms!

4.4 Direct Tests on Asymmetric Stickiness

In this subsection, we perform direct tests for the different stickiness of borrowers and lenders under two shocks: the Ezubao fraud, and platform failures.

4.4.1 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 exogenous shock to examine the borrower's' and lenders' stickiness.

Specifically, we choose a 16-week window centered around the Ezubao closure date and use a difference-in-differences specification to study the stickiness of borrowers relative to lenders:

$$lnN_{i,t}^{player} = b_0 + b_1 dummy1 + b_2 dummy2 + b_3 dummy1 \times dummy2 + b_4 I_{i,t} + b_5 lnLS_{i,t} + b_6 lnIA_{i,t} + PlatformFixedEffect + u_{i,t}, \qquad (8)$$

where $dummy1$ 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. The coefficient on the difference-in-difference effect, b_3, therefore presents the difference in the leaving rates between borrowers and lenders.

Table 7 shows a positive coefficient of the difference-in-difference 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 model assumption.

4.4.2 Large-sample Analysis of Departures Preceding Platform Failures

Next, we 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 a different eagerness to leave. Panel A of Table 8 reports the change of log numbers of borrowers and lenders up to 6

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

months before platform failures. Particularly, we first take the log of the average borrower's or lenders' number in a certain month before a platform's failure, we then take the difference to its previous month.

Panel A of Table 8 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% (t-statistics 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 8, 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.

Note that the average leaving rate (9.9%) for lenders during the half-year before the platform failure is much larger than the lenders' entering rate (3.7%) during the half-year after the platform birth. This indicates that lenders are afraid of the failure of the platform and thus avoid stay on a failing platform. In contrast, the leaving and entering rates during the half-year before the failure and half-year after the birth are rather similar (6.9% v.s. 4.7%), which, again, indicates that borrowers are rather less motivated to leave the platform.

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, consistent with the notion that borrowers have a stronger stickiness, and therefore, prefer to stay at the platform for a longer time.

These features potentially lead to the two observed asymmetries in our data. However, to see the mechanisms clearly, we need a model of two-sided platforms with endogenous platform failures, which can capture the distinguishing features of financial platforms.

5. A Model of Two-sided Financial Platforms with Endogenous Platform Failures

In this section, we first present a model to explain the asymmetric CNEs and offer a rich set of testable predictions.

5.1 Model Setup

We start with a single platform, a continuum of lenders and a continuum of borrowers. For simplicity, lenders all lend the same amount and borrowers borrow the same amount. The interaction proceeds in several steps in the model. First, given a platform's installed base, the platform owner sets fees. Then potential lenders and borrowers decide to participate simultaneously. The platform owner collects fees and loans are made. Finally, borrowers complete their projects, the platform either survives or fails, and the payoffs to borrowers and lenders are realized.

Let $\widehat{N}_b$ and $\widehat{N}_l$ be the installed bases for borrowers and lenders respectively from the start of the interaction. Let N_b and N_l be new borrowers and lenders. If N_b or N_l takes a negative value, it implies users from the installed base leaving. Let $\lambda(\widehat{N}_b, \widehat{N}_l, N_b, N_l, s) = F(\widehat{N}_b, \widehat{N}_l, N_b, N_l) + G(s)$ denote a platform's survival probability by the end of the period, where F is differentiable to the second order and G is increasing. s is the end of period sentiment about the platform, it could be affected by government policies, idiosyncratic shocks, platform age, userbase trend, etc. Importantly, s can only be imperfectly forecasted when agents make decisions. For model simplicity, suppose s is either H (optimistic) or L (pessimistic).

Building on the seminal work of Rochet and Tirole (2003), and Armstrong (2006), we define the utilities for the lenders and borrowers, respectively:

$$\begin{aligned} U_l &= \alpha(s)\widehat{N}_b + \lambda k - (1-\lambda) - P_l = \alpha(s)\widehat{N}_b + \lambda(1+k) - 1 - P_l \\ U_b &= \beta(s)\widehat{N}_l - \lambda k + (1-\lambda) - P_b = \beta(s)\widehat{N}_l - \lambda(1+k) - 1 - P_b \end{aligned} \tag{9}$$

The fact the utilities only depend on the installed base corresponds to the empirical measure of CNEs in the literature and in our empirical analysis. It can be interpreted new borrowers search for funding from installed lenders (who are known to be on the platform) and new lenders look at projects posted by (installed) existing borrowers.

k is a market-based interest rate that is exogenous to the model. One interpretation is that lenders and borrowers set interests only after being matched and k is set by the one-to-one bargaining; another interpretation is that k is set by the P2P lending market in general. Because our data do not allow us to analyze interest rates for different loans, we use exogenous k but instead allows the number of lenders and borrowers to be endogenous.

We set $\beta(H) = \beta$ and $\beta(L) = (1 - c)\beta$, where $c \in (0, 1)$. When $s = L$, existing lenders can leave the platform very easily, installed base have a smaller benefit to potential borrowers. That said, $\alpha(H) = \alpha(L) = \alpha$ because borrowers face significant frictions when leaving as those when onboarding. For example, the onboarding process at a new platform is once again elaborate and costly. Due to data propriety, privacy, and storage segmentation, borrowers also find it hard to transfer their credit to a different platform and thus lose their accumulated reputation when leaving. As such, even though they may want to leave more during an adversarial market environment $(s = L)$, While onboarding is still difficult (from fundraising or learning about the platform and projects), leaving the platform for lenders is very easy.

The participation functions are given by,

$$N_b = \frac{1}{Z} U_b - \widehat{N}_b$$
$$N_l = \frac{1}{Z} U_l - \widehat{N}_l \tag{10}$$

Where N_b and N_l are new customers. Z is the upper bound for achievable utility (any utility exceeding Z would be treated as having Z utility).

We adopt a general form of λ increasing in installed userbase and weakly increasing in new users. The more users (old and new) on the platform, the more likely the platform will survive. Mathematically,

$$\frac{\partial\lambda}{\partial\widehat{N}_b} > 0, \qquad \frac{\partial\lambda}{\partial\widehat{N}_l} > 0$$
$$\frac{\partial\lambda}{\partial N_b} \geq 0, \qquad \frac{\partial\lambda}{\partial N_l} \geq 0 \tag{11}$$

Note that we allow higher-order effects and that the two sides could have strategic complementarity or substitutability for the platform's survival. In addition, we make a technical assumption that Z is large enough that for the exogenously given survival function λ, the increased probability of platform survival when the number of lenders increases decreases borrowers' utility (although borrowers' utility overall can still be higher because of greater network externalities from lender increases). This is natural and requires the coefficient of $\frac{\partial\lambda}{\partial\widehat{N}_l}$ in the expression of $\frac{\partial U_b}{\partial\widehat{N}_l}$ be negative, which translates into $Z > \frac{1+k}{2}(\frac{\partial\lambda}{\partial N_b} + \frac{\partial\lambda}{\partial N_l})$. Intuitively, we expect borrowers get hurt when the platform failure probability is lower because now they more likely have to pay back the loans. This assumption basically captures (as would be clear from the proofs in the appendix) that this direct negative effect on borrowers is not dominated by the indirect positive effect the lowered failure probability has for lenders' utility which leads to potential reductions in equilibrium borrower fees.

The platform owner's expected profit is

$$\begin{aligned}\pi(U_l, U_b) = E[[N_b + \widehat{N}_b]\,&\overbrace{[\beta(s)\widehat{N}_l - \lambda(1+k) + 1 - U_b - f_b]}^{P_b - f_b} \\ &+ [N_l + \widehat{N}_l]\,\overbrace{[\alpha(s)\widehat{N}_l + \lambda(1+k) - 1 - U_l - f_l]}^{P_l - f_l}]\end{aligned} \tag{12}$$

Where f_b and f_l are service costs per borrower and per lender. We allow the platform owner to maximize profit over the fees she sets, which essentially varies the utilities lenders and borrowers get.

Proposition 1. ***[First Asymmetry]*** *Only the lenders' CNE is higher for* $s = H$ *than for* $s = L$, *i.e.*,

$$\frac{\partial N_b}{\partial \hat{N}_l}\bigg|_{s=H} > \frac{\partial N_b}{\partial \hat{N}_l}\bigg|_{s=L} \quad \text{and} \quad \frac{\partial N_l}{\partial \hat{N}_b}\bigg|_{s=H} = \frac{\partial N_l}{\partial \hat{N}_b}\bigg|_{s=L} \tag{13}$$

The proof of Proposition 1 is shown in Appendix C.

The proposition implies during the first year of a platform's launch or when the user base is increasing or when the platform is large (situations in which it is more likely $s = H$), lenders' CNE is higher than that during the year leading to a platform's demise or when the user base is decreasing or when the platform is small and unstable (situations in which it is more likely $s = L$). This is consistent with the empirical evidence in Sections 3.

Corollary 1.1 *Lenders' CNE is predictive of* s.

Because s is not directly observed until the end of the period, the value of lenders' CNE reveals incremental information about s due to their positive correlation.

Corollary 1.2 $\frac{\partial N_l}{\partial \hat{N}_b} - \frac{\partial N_b}{\partial \hat{N}_l}$ *is decreasing in* s.

Corollary 1.2 implies that we should see the difference between borrowers' CNE and lenders' CNE to be bigger on smaller, declining, or failing platforms. This also begs the question if this difference is always positive.

Proposition 2 [Second Asymmetry] *Borrowers' CNE is bigger than lenders' CNE when* $\frac{\partial^2 \lambda}{\partial \hat{N}_b \partial N_b} = \frac{\partial^2 \lambda}{\partial \hat{N}_l \partial N_l} = 0$ *and* $\frac{\partial^2 \lambda}{\partial \hat{N}_b \partial N_l} = \frac{\partial^2 \lambda}{\partial \hat{N}_l \partial N_b}$. *Corollary 1.2 further implies that the gap is bigger under adverse market conditions.*

The proof of Proposition 2 is shown in Appendix C.

The conditions are sufficient but not necessary. They are mild in that they simply require that utility upper bound, Z, is sufficiently big, same-side users do not have increasing or decreasing impacts on λ, and λ has symmetric dependence on the two sides.

To get the intuition, let us look at a special case in which platform λ only depends on the installed base,

$$\frac{\partial \lambda}{\partial N_b} = \frac{\partial \lambda}{\partial N_l} = 0$$

We can compute the CNEs as,

$$
\begin{aligned}
\frac{\partial N_l}{\partial \widehat{N}_b} &= \frac{1}{Z}\frac{\partial U_l}{\partial \widehat{N}_b} = \frac{\alpha(s) + (1+k)\dfrac{\partial \lambda}{\partial \widehat{N}_b}}{2Z} > \frac{\alpha(s)}{2Z} \\
\frac{\partial N_b}{\partial \widehat{N}_l} &= \frac{1}{Z}\frac{\partial U_b}{\partial \widehat{N}_l} = \frac{\beta(s) - (1+k)\dfrac{\partial \lambda}{\partial \widehat{N}_l}}{2Z} < \frac{\beta(s)}{2Z}
\end{aligned}
\tag{14}
$$

Because lenders enjoy the diversification benefit in addition to the matching efficiency gain brought by the cross-side network effect, $\alpha > \beta$ in general. Moreover, note that without platforms' failure, lenders and borrowers' CNEs are $\frac{\beta(s)}{2Z}$ and $\frac{\alpha(s)}{2Z}$ respectively. So we can see that the potential platform failure adds to the gap between borrowers' CNE and lenders' CNE. Once again, this effect is rare on non-financial platforms because failures on non-financial platforms affect the two sides of the market to similar extents, whereas, for financial platforms, failures during the contracts are a boon to borrowers who no longer need to pay back. Finally, the gap is further widened for $s = L$ because $\beta(L)$ is smaller than $\beta(H)$. This also immediately implies that lenders' CNE is higher for $s = H$ and can be used to predict *s*.

Note that for non-financial platforms, $\beta(L)$ would not be significantly smaller because the buyer (money provider) can return a good with false claims immediately because of the spot nature of the interactions. That means that most non-financial platforms maintain a reputation system for buyers as well as for sellers to prevent buyers from unfairly taking advantage of the sellers' or platforms' return policies. But for financial platforms, due to the non-trivial duration of the contracts, if sellers do not pay back, the platforms are typically not responsible for recovering the lenders' principles.

Now it should be clear that the CNE asymmetries can be largely attributed to the unique features of financial platforms. We, therefore, contribute to the theory of two-sided platforms by not only modeling platform failures for the first time but also highlighting the unique features of financial platforms and their implications.

5.2. Further Predictions

Our model generates several predictions, which we list below and test in our data in the next section:

- Lenders' CNEs predict negatively forecasts platform failure (extensive margin).

To see this, we note that lenders' CNEs are correlated with platform status, which in turn enters the platform's survival likelihood.

- Lenders' CNEs positively correlates with the final platform scale (intensive margin).

To see this, we can add up the number of lenders and borrowers and show the correlation. This also implies if lenders' CNEs are persistent, then CNEs in trailing months can be used to predict future platform scale in a dynamic environment.

- Platform's initial scale (or sum of installed lenders and borrowers) can help predict platform eventual failure (interaction of intensive and extensive margin).

To see this, we note that the installed base positively correlates with the number of new users. Given that all users (installed or new) contribute to the survival probability, scale helps with predicting survival likelihood.

6. Model Predictions and Implications

As predicted by the model, since lenders' CNEs are different in periods of growth and decline, they should have predictability on the platform growth and its failure. On the contrary, borrowers' CNEs do not have these predictions because of their symmetric nature.

Note that in this section, we mainly utilize the Fama-Macbeth regression to analyze the predictability of lenders' CNEs on the cross-sectional difference of the platforms and use the Newey-West method to adjust the standard errors of the estimation coefficients.

6.1 CNEs and Dynamics of Platform Scale

We now formally analyze the predictability of CNEs on the growth and decline of platforms. As the major goal of a platform is to facilitate trading, trading volume enhancement is thus one important target for a successful platform. We, therefore, focus on the change of trading volumes in a certain platform. We perform a Fama-MacBeth regression with a monthly frequency:

$$\Delta lnV_{i,t+1} = b_0 + b_1 CNE_{i,t}^{Borrower} + b_2 CNE_{i,t}^{Lender} + b_3 lnV_{i,t} + controls + CalendarYearDummy + u_{i,1}, \quad (15)$$

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

Panel A of Table 9 shows that lenders' CNE has a positive and significant predictability on the platform trading volume of the next month. This effect is consistently positive for all specifications in Panel A and corroborates our model predictions. 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 trading volume the next month (more than 13% on an annual basis). Using a different way of lining up platforms as a robustness check, Panel B is consistent with the result in Panel A.

One caveat to the exercise is that the predictions are subject to selection bias and one can use the Heckman correction to resolve the issue.

6.2 CNEs and Platform Failures

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

$$FA_{i,t+1} = c_1 CNE_{i,t}^{Lender} + c_2 CNE_{i,t}^{Borrower} + c_3 lnV_{i,t} + controls + CalendarYearDummy + u_{i,t+1} \quad (16)$$

$FA_{i,t}$ is a dummy variable, which is set to 1 when the platform fails at the tth month, and 0 otherwise. Panel A of Table 10 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). 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 manifests: larger lenders' CNEs result in a reduction of a platform's future failure rate significantly at the 1% level.

Moreover, Table 10 also documents that the large platform (represented by large trading volumes) lowers the failure probability, one standard increase of the platform size reduces the failure probability by 1.7% in the next month (20% annually).

These results are consistent with the model implications: both lenders' CNEs and platform scales are important in forecasting the survival of P2P platforms.

6.3 Early Prediction of Long-run Survival

Lenders' CNEs are a good proxy for the ability to attract borrowers and predict borrower increases in the one-period model. In a dynamic setting, if CNEs are persistent, this implies that lenders' CNEs may indicate a platform's ability to attract borrowers in the long run. As mentioned before, platforms that survival beyond inception typically rely on attracting borrowers because borrowers are sticky and help reduce failure rates. Therefore, in this section, we directly test the link between the early-period lenders' CNEs and the destiny (long-run failure or survival) of platforms. Specifically, we examine how CNEs calculated from the first year of a platform launch affects the default rate in its future life:

$$FA_{i,1} = b_0 + b_1 CNE_{i,0}^{Borrwer} + b_2 CNE_{i,0}^{Lender} + b_3 lnV_{i,0} + b_4 I_{i,0} + b_5 lnLS_{i,0} + b_6 lnIA_{i,0} + u_{i,1}, \tag{17}$$

where $CNE_{i,0}^{Lender}$ and $CNE_{i,0}^{Borrower}$ are the lenders' and borrowers' CNEs calculated for the first year of the ith platform. Variables $lnV_{i,0}$, $I_{i,0}$, $lnLS_{i,0}$ and

$lnIA_{i,0}$ are log trading volume, interest rates, log loan size, and log investing amount per lender averaged within the first year of the i[th] platform, respectively. $FA_{i,1}$ is a dummy variable, which is set to 1 when the i[th] platform failed after the first year until the end of the 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. In particular, we assume the hazard rate $h_{i,1}$ of the i[th] platform after the first year is as follows:

$$h_{i,1} = b_0 + b_1 CNE_{i,0}^L + b_2 CNE_{i,0}^B + b_3 lnV_{i,0} + b_4 I_{i,0} + b_5 lnLS_{i,0} + b_6 lnIA_{i,0} + u_{i,1} \tag{18}$$

Table 11 reports the results. It is somewhat impressive 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 capabilities 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.

In the meanwhile, a low trading volume at the beginning also foretells a high rate of failure: one standard deviation increase in platform scales reduces 12.7% of the probability of platform failure.

In a sense, a platform has its destiny at birth, given its initial lenders' CNE and platform scale. 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.[17]

[17] From the regression, we also see 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.

6.4 Business and Regulatory Implications

As mentioned before, getting borrowers are more important than lenders for P2P platforms due to their reluctance-to-leave. 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 more sticky than lenders on such financial platforms, potentially stabilizing platforms, especially during negative shocks. Under fierce competition in this emerging industry, *the acquisition of borrowers (sticky side) using existing funding sources is the key to P2P platforms' 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.[18]

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.

A better understanding of the role of platform CNEs can, therefore, assist regulators. For example, regulators can closely monitor lenders' CNEs to anticipate platform failures. They can also disclose platform statistics such as trading volumes 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.[19] Similarly, venture investors of the platforms and lenders can also monitor lenders' CNEs to better manage their risks.

7. Conclusion

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

[19] 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 investigate how financial platforms differ from non-financial platforms and how cross-side network effects (CNEs) affect platform dynamics, using a large panel data of P2P lending platforms in China. We measure the cross-side network effects on P2P lending platforms using the elasticity of participation from one side on the number of users from the other side, and document persistent CNEs on both sides of the market. While lenders' CNEs are asymmetrically bigger on new, growing, and larger platforms than on failing, declining, or smaller platforms, borrowers' CNEs exhibit no such asymmetry. Moreover, borrowers' CNEs are in general larger than lenders' CNEs, especially on failing, declining, or small platforms. These asymmetries reflect unique features of financial platforms such as risk diversification benefit for lenders with a greater number of borrowers, inherent differences between lenders and borrowers' risks as money receivers and payers, and borrowers' stickiness due to contracting frictions.

To rationalize the patterns, we build a model of two-sided platforms incorporating endogenous platform failures and the aforementioned distinguishing features of financial platforms. The model highlights asymmetric CNEs and offers a number of predictions, which we verify in the data. For example, lenders' CNEs can predict the future failure of P2P platforms (extensive margin), even at a very early stage; they also predict future platform scale (intensive margin). Scale also forecasts future platform survival likelihood (interaction of intensive and extensive margins). Our study not only advances the fundamental understanding of two-sided platforms and FinTech marketplaces, but also provides guidance for platform owners, 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. 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: P2P Platforms with Different Starting Years

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
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
Origination Time (seconds, log)	9.596	2.459	8.951	2.573	10.455	2.002
Loan Concentration	69.3%	28.8%	57.6%	30.7%	81.6%	20.4%

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 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 t[th] week of platform i's lifetime, respectively; $CN_{i,t}^{Lender}$ and $CN_{i,t}^{Borrower}$ are the cumulative numbers of lenders and borrowers in the past four weeks (from the week of t-3 to t). $I_{i,t}$, $LS_{i,t}$ and $LA_{i,t}$ are interest rates, loan size and investment per lender averaged at the t[th] week on the i[th] 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. The correlation between borrowers' and lenders' CNEs are 0.47 and 0.53, respectively, for failed and live platforms.

	Failed Platforms		**Live Platforms**	
	Borrowers' CNE, b_1	**Lenders' CNE, c_1**	**Borrowers' CNE, b_1**	**Lenders' CNE, c_1**
Average	0.257	0.229	0.302	0.330
Std Dev	0.356	0.309	0.302	0.296
Max	1.345	2.274	1.454	1.330
Min	-0.939	-0.591	-0.633	-0.383
Positive (%)	78.0%	79.5%	85.7%	89.6%
Negative (%)	22.0%	20.5%	14.3%	10.4%
Positive with 95% significance (%)	34.7%	35.5%	49.7%	55.3%
Negative with 95% significance (%)	2.6%	0.5%	2.1%	0.4%
Non-significance (%)	62.7%	64.0%	48.2%	44.3%

Table 3. CNEs throughout Platforms' 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 Inception (P1)	The Middle One Year (P2)	One Year before Failure (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 the panel regression:

$$CNE_{i,t}^{Player} = b_1 Negative(\Delta V_{i,t}) + b_2 ln\ V_{i,t} + controls + YearFixedEffect + PlatformFixedEffect + u_{i,t+1}$$

where *player* is either lender or borrower, $CNE_{i,t}^{Player}$ is the player's (lenders' or borrower's) CNEs at t^{th} month of the i^{th} platform computed with a rolling one-year window. $\Delta V_{i,t} = V_{i,t} - V_{i,t-12}$ is the change of the player's number from the past year. $Negative(x)$ is 1 when x is negative and zeros otherwise. The control variables are interest rates, log loan size and log investing amount averaged within the t^{th} month on the i^{th} platform, respectively. Quantities in brackets are the t-statistics.

	Borrowers' CNE	Lenders' CNE
$\boldsymbol{Negative(\Delta V_{i,t})}$	-0.021	-0.058
	(-0.77)	(-8.22)
$\boldsymbol{lnV_{i,t}}$	0.002	0.010
	(0.23)	(5.53)
$\boldsymbol{I_{i,t}}$	-0.880	-0.468
	(-2.29)	(-4.32)
$\boldsymbol{lnLS_{i,t}}$	-0.004	-0.021
	(-0.36)	(-7.03)
$\boldsymbol{lnIA_{i,t}}$	-0.003	0.009
	(-0.25)	(2.60)
Calendar Year Dummy	Yes	Yes
Platform Fixed Effect	Yes	Yes
$\mathbf{R^2}$	0.00%	0.8%

Table 5. CNE Spread and Platform Size

In this table, we run the panel regression:

$$CNE_{i,t}^{Borrower} - CNE_{i,t}^{Lender} = b_0 + b_1 Negative\left(\Delta V_{i,t}\right) + b_2 \ln\left(V_{i,t}\right) + controls + u_{i,t+1}$$

The control variables are interest rates, log loan size and log investing amount in the t^{th} month on the i^{th} platform, respectively. Quantities in brackets are the t-statistics.

	CNE Spread (Borrower-Lender)	
Const	0.021	0.124
	(1.58)	(4.98)
$\boldsymbol{Negative}(\Delta \boldsymbol{V}_{i,t})$	0.018	0.014
	(2.32)	(1.76)
$\boldsymbol{ln}\,(\boldsymbol{V}_{i,t})$	-0.009	-0.014
	(-4.74)	(-6.88)
$\boldsymbol{I}_{i,t}$		-0.703
		(-6.01)
$\boldsymbol{lnLS}_{i,t}$		0.006
		(2.00)
$\boldsymbol{lnIA}_{i,t}$		-0.003
		(-0.71)
R^2	0.2%	0.4%

Table 6 Player Numbers, Matching Efficiency and Risk Diversification

This table reports the benefit of large platform scales via matching efficiency and risk diversification by running the following three panel regressions:

$$lnM_{i,t+1} = d_1 lnN_{i,t}^{player} + d_2 I_{i,t} + d_3 lnLS_{i,t} + d_4 lnIA_{i,t} + d_5 lnM_{i,t} + YearFixedEffect + PlatformFixedEffect + u_{i,t+1}$$

$$CT_{i,t+1} = d_1 lnN_{i,t}^{player} + d_2 I_{i,t} + d_3 lnLS_{i,t} + d_4 lnIA_{i,t} + d_5 CT_{i,t} + YearFixedEffect + PlatformFixedEffect + u_{i,t+1}$$

$$lnDI_{i,t+1} = d_1 CT_{i,t} + d_2 lnN_{i,t}^{Lender} + d_3 I_{i,t} + d_4 lnLS_{i,t} + d_5 lnIA_{i,t} + d_6 lnDI_{i,t} + YearFixedEffect + PlatformFixedEffect + u_{i,t+1}$$

where $M_{i,t}$ is the average origination time (in seconds) that a project has achieved its full-scale amount on the i[th] platform at the t month, and $CT_{i,t}$ and $DI_{i,t}$ are the percentage of top 10 loans and the average amount per investment, respectively, in the i[th] platform at the t[th] month. $I_{i,t}$, $LS_{i,t}$ and $LA_{i,t}$ are interest rates, loan size lender averaged at the t[th] month on the i[th] platform, respectively. $N_{i,t}^{player}$ is the number of the player (borrower or lender) at month t in platform i. Quantities in brackets are the t-statistics.

Panel A: Player's Numbers and Matching Efficiency

	Log of Origination Time	
$lnN_{i,t}^{borrower}$	-0.127	
	(-12.45)	
$lnN_{i,t}^{lender}$		-0.115
		(-13.39)
$I_{i,t}$	-1.540	-0.872
	(-4.77)	(-2.88)
$lnLS_{i,t}$	-0.022	0.111
	(-1.74)	(7.50)
$lnIA_{i,t}$	0.059	-0.095
	(4.24)	(-5.19)
$lnM_{i,t}$	0.858	0.851
	(163.51)	(154.92)
Calendar Year Dummy	Yes	Yes
Fixed Effect	Yes	Yes
R^2	81.8%	81.7%

Panel B: Player's Numbers and Concentration

	Loan Concentration	
$lnN_{i,t}^{borrower}$	-0.011	
	(-9.86)	
$lnN_{i,t}^{lender}$		-0.008
		(-8.42)
$I_{i,t}$	0.028	0.050
	(0.73)	(1.35)
$lnLS_{i,t}$	-0.002	0.007
	(-1.85)	(6.12)
$lnIA_{i,t}$	0.001	-0.006
	(1.21)	(-4.23)
$CT_{i,t}$	0.916	0.933
	(159.17)	(193.60)
Calendar Year Dummy	Yes	Yes
Fixed Effect	Yes	Yes
R^2	91.9%	91.9%

Panel C: Loan Concentration and Investor's Diversification

	Average Amount per Investment	
$CT_{i,t}$	0.096	0.044
	(7.47)	(3.33)
$lnN_{i,t}^{lender}$		-0.017
		(-3.93)
$I_{i,t}$		-0.203
		(-1.60)
$lnLS_{i,t}$		0.027
		(4.94)
$lnIA_{i,t}$		0.013
		(1.14)
$lnDI_{i,t}$	0.925	0.883
	(138.41)	(61.90)
Calendar Year Dummy	Yes	Yes
Fixed Effect	Yes	Yes
R^2	86.6%	86.8%

Table 7. 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:

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

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. $I_{i,t}$, $lnLS_{i,t}$ 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
$\mathbf{R^2}$	73.8%	74.3%

Table 8. Leaving Players 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 lenders' 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 9. CNEs and Platform Growth

This table reports the predictability of borrower's and lenders' CNEs on the growth of trading volumes via the Fama-MacBeth regression:

$$\Delta lnV_{i,t+1} = b_0 + b_1 CNE_{i,t}^B + b_2 CNE_{i,t}^L + b_3 lnV_{i,t} + Controls + TimeDummy + u_{i,1}$$

$V_{i,t+1}$ is the trading volume at the t+1 month for the i[th] platform. $CNE_{i,t}^L$ and $CNE_{i,t}^B$ are the lenders' and borrowers' CNEs, respectively, calculated with a one-year rolling window. In Panel A, t is indexed by the lifetime 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)**
$\boldsymbol{NE_{i,t}^B}$	0.009		-0.003
	(2.180)		(-0.803)
$\boldsymbol{NE_{i,t}^L}$		0.026	0.029
		(6.540)	(8.881)
$\boldsymbol{lnV_{i,t}}$	-0.020	-0.021	-0.020
	(-7.909)	(-9.574)	(-8.091)
Controls	Yes	Yes	Yes
Calendar Year Dummy	Yes	Yes	Yes
$\mathbf{R^2}$	3.0%	3.1%	3.4%

Panel B: 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 10. CNEs and Platform Failure

This table reports the predictability of borrower's and lenders' CNEs on platform failure via the Fama-MacBeth regression:

$$lnFA_{i,t+1} = c_0 + c_1 CNE_{i,t}^{L} + c_2 CNE_{i,t}^{B} + c_3 lnV_{i,t} + Controls + TimeDummy + u_{i,t+1}$$

$FA_{i,t+1}$ is a dummy variable that equals one when the i[th] platform fails at month t+1, and 0 otherwise. $CNE_{i,t}^{L}$ and $CNE_{i,t}^{B}$ are the lenders' and borrowers' CNEs, respectively, calculated with a one-year rolling window. In Panel A, t is indexed by the lifetime 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		
$NE_{i,t}^{B}$	-0.002		0.002	-0.089		0.089
	(-1.194)		(0.937)	(-1.823)		(1.124)
$NE_{i,t}^{L}$		-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 11. Early-stage CNEs and P2P Platform Failure

This table shows how the first year CNEs of a platform will influence the future default in its future life:

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

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

Figures

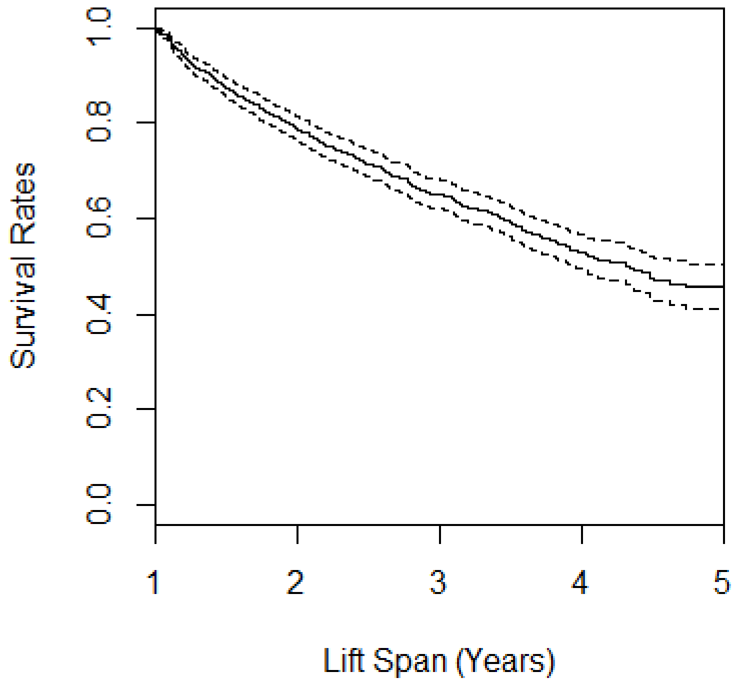

Figure 1 Kaplan-Meier Survival Rate vs. Platform Lifespan
The dotted line shows the 95% confidence levels.

Appendix A. Institutional details on P2P lending

A.1. 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.[20] 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.[21]

A.2. China's P2P history, growth, and 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 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).

[20] See www.lendingclub.com.
[21] See https://www.bloomberg.com/quicktake/peer-peer-lending.

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.[22] 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.

A.3. 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 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

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

money on the due date, sometimes, a third party (the insurance company) might be involved to help recover the lenders' loss.

A.4. 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.

A.5. 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.

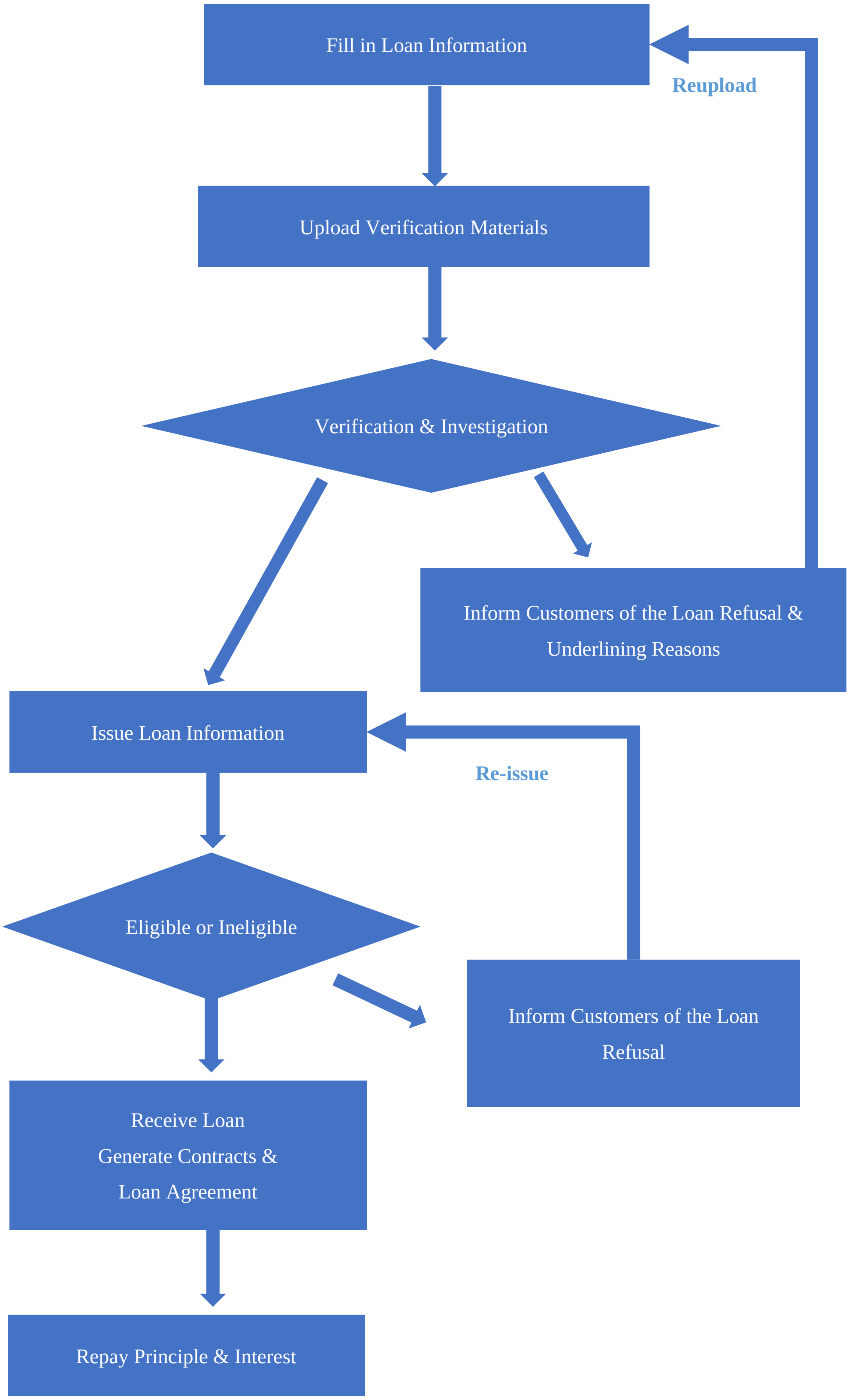

Figure A1. Flow Chart of the Loan Application Process.

A.6. 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 A References

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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)
$\mathbf{log}(\boldsymbol{GDP})$	0.066	0.038
	(1.284)	(0.922)
$\mathbf{log}(\boldsymbol{Population})$	0.088	0.080
	(2.799)	(3.157)
Launch Year Dummy	Yes	Yes
$\mathbf{R^2}$	3.64%	3.33%

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

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

Table 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. Asymmetric CNEs: A Fama-Macbeth Approach

This table runs a Fama-MacBeth regression to find the asymmetric properties of CNEs:

$$CNE_{i,t}^{Player} = b_0 + b_1 Negative(\Delta V_{i,t}) + b_2 lnV_{i,t} + controls + CanlenderYearDummy + u_{i,t+1}$$

where *player* is either lender or borrower, $CNE_{i,t}^{Player}$ is the player's (lenders' or borrower's) CNEs at the *t*th month of the *i*th platform lifetime, calculated with a rolling one-year window. $\Delta lnV_{i,t} = lnV_{i,t} - lnV_{i,t-12}$ is the change of the platform's trading volume from t-12 to t. $Negative(x)$ is 1 when x is negative and zeros otherwise. The control variables are interest rates, log loan size and log investing amount averaged within the tth month on the ith platform, respectively. 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.

	Borrowers' CNE	Lenders' CNE
$\boldsymbol{Negative(\Delta V_{i,t})}$	0.007	-0.035
	(0.396)	(-2.501)
$\boldsymbol{lnV_{i,t}}$	0.018	0.027
	(1.879)	(6.448)
$\boldsymbol{I_{i,t}}$	-0.431	-0.318
	(-0.927)	(-1.797)
$\boldsymbol{lnLS_{i,t}}$	-0.030	-0.046
	(-5.342)	(-12.283)
$\boldsymbol{lnIA_{i,t}}$	0.001	0.022
	(0.499)	(3.346)
Calendar Year Dummy	yes	yes
$\mathbf{R^2}$	3.98%	4.0%

Table B.4. CNEs Gaps: A Fama-Macbeth Approach

This table runs a Fama-MacBeth regression to find the asymmetric properties of CNEs:

$$CNE_{i,t}^{Borrower} - CNE_{i,t}^{Lender} = b_0 + b_1 Negative(\Delta V_{i,t}) + b_2 lnV_{i,t} + controls + CanlenderYearDummy + u_{i,t+1}$$

where *player* is either lender or borrower, $CNE_{i,t}^{Player}$ is the player's (lenders' or borrower's) CNEs at the t^{th} month of the i^{th} platform lifetime, calculated with a rolling one-year window. $\Delta lnV_{i,t} = lnV_{i,t} - lnV_{i,t-12}$ is the change of the platform's trading volume from t-12 to t. $Negative(x)$ is 1 when x is negative and zeros otherwise. The control variables are interest rates, log loan size and log investing amount averaged within the t^{th} month on the i^{th} platform, respectively. 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 Spread (Borrower-Lender)	
Const	0.159	0.200
	(2.231)	(1.469)
$\boldsymbol{Negative(\Delta V_{i,t})}$	0.016	0.012
	(1.352)	(1.501)
$\boldsymbol{ln\ (V_{i,t})}$	-0.024	-0.020
	(-2.577)	(-2.781)
$\boldsymbol{I_{i,t}}$		0.052
		(0.083)
$\boldsymbol{lnLS_{i,t}}$		-0.026
		(-1.137)
$\boldsymbol{lnIA_{i,t}}$		0.037
		(1.122)
$\mathbf{R^2}$	3.6%	10.2%

Appendix C: Proofs of Propositions

Proof of Proposition 1.

Proof. The platform owner's expected profit is

$$\pi(U_l, U_b) = \mathbb{E}[[N_b + \hat{N}_b]\overbrace{[\beta(s)\hat{N}_l - \lambda(1+k) + 1 - U_b - f_b]}^{P_b - f_b} + [N_l + \hat{N}_l]\overbrace{[\alpha(s)\hat{N}_l + \lambda(1+k) - 1 - U_l - f_l]}^{P_l - f_l}] \tag{1}$$

For simplification, α and β denote $\alpha(s)$ and $\beta(s)$ in the following steps. F.O.C. w.r.t. U_b gives,

$$\frac{[\beta\hat{N}_l - \lambda(1+k) + 1 - U_b - f_b]}{Z} - \frac{U_b}{Z} - \frac{1+k}{Z}\frac{\partial\lambda}{\partial N_b}[\frac{U_b - U_l}{Z}] = 0$$

Combine with

$$U_l = \alpha\hat{N}_b + \lambda k - (1-\lambda) - P_l = \alpha\hat{N}_b + \lambda(1+k) - 1 - P_l \tag{2}$$

and

$$U_b = \beta\hat{N}_l - \lambda k + (1-\lambda) - P_b = \beta\hat{N}_l - \lambda(1+k) - 1 - P_b \tag{3}$$

we can get

$$P_b = f_b + U_b + \frac{1+k}{Z}\frac{\partial\lambda}{\partial N_b}[U_b - U_l]$$

Similarly,

$$P_l = f_l + U_l + \frac{1+k}{Z}\frac{\partial\lambda}{\partial N_l}[U_b - U_l]$$

Then

$$\begin{aligned}\frac{\partial U_l}{\partial\hat{N}_b} &= \alpha + (1+k)\frac{\partial\lambda}{\partial\hat{N}_b} - \frac{\partial P_l}{\partial\hat{N}_b}\\ &= \alpha + (1+k)\frac{\partial\lambda}{\partial\hat{N}_b} - \frac{\partial U_l}{\partial\hat{N}_b} + \frac{1+k}{Z}\frac{\partial\lambda}{\partial N_l}(\frac{\partial U_l}{\partial\hat{N}_b} - \frac{\partial U_b}{\partial\hat{N}_b}) + \frac{1+k}{Z}\frac{\partial^2\lambda}{\partial N_l\partial\hat{N}_b}[U_l - U_b]\end{aligned}$$

This implies

$$\left[2 - \frac{1+k}{Z}\frac{\partial\lambda}{\partial N_l}\right]\frac{\partial U_l}{\partial\hat{N}_b} = \alpha + (1+k)\frac{\partial\lambda}{\partial\hat{N}_b} - \frac{1+k}{Z}\frac{\partial\lambda}{\partial N_l}\frac{\partial U_b}{\partial\hat{N}_b} + \frac{1+k}{Z}\frac{\partial^2\lambda}{\partial N_l\partial\hat{N}_b}[U_l - U_b] \tag{4}$$

Note that with the technical assumption on λ and Z, the denominator is positive. From Equation (3),

$$\frac{\partial U_b}{\partial\hat{N}_b} = \frac{-(1+k)\frac{\partial\lambda}{\partial\hat{N}_b} + \frac{1+k}{Z}\frac{\partial\lambda}{\partial N_b}\frac{\partial U_l}{\partial\hat{N}_b} + \frac{1+k}{Z}\frac{\partial^2\lambda}{\partial N_b\partial\hat{N}_b}[U_l - U_b]}{2 + \frac{1+k}{Z}\frac{\partial\lambda}{\partial N_b}} \tag{5}$$

After substituting (5) into (4), we get,

$$\frac{\partial U_l}{\partial \hat{N}_b} = \frac{\alpha + (1+k)\frac{\partial \lambda}{\partial \hat{N}_b} - \frac{1+k}{Z}\frac{\partial \lambda}{\partial N_l}\left\{\frac{-(1+k)\frac{\partial \lambda}{\partial \hat{N}_b} + \frac{1+k}{Z}\frac{\partial \lambda}{\partial N_b}\frac{\partial U_l}{\partial \hat{N}_b} + \frac{1+k}{Z}\frac{\partial^2 \lambda}{\partial N_b \partial \hat{N}_b}[U_l - U_b]}{2 + \frac{1+k}{Z}\frac{\partial \lambda}{\partial N_b}}\right\} + \frac{1+k}{Z}\frac{\partial^2 \lambda}{\partial N_l \partial \hat{N}_b}[U_l - U_b]}{2 - \frac{1+k}{Z}\frac{\partial \lambda}{\partial N_l}}$$

Rearranging and simplifying, we get**:**

$$\frac{\partial U_l}{\partial \hat{N}_b} = \frac{\alpha + \left\{\frac{(1+k)\frac{\partial \lambda}{\partial \hat{N}_b}\left(2 + \frac{1+k}{Z}\left(\frac{\partial \lambda}{\partial N_b} + \frac{\partial \lambda}{\partial N_l}\right)\right) + \frac{(1+k)^2}{Z^2}\frac{\partial \lambda}{\partial N_l}\frac{\partial^2 \lambda}{\partial N_b \partial \hat{N}_b}[U_b - U_l]}{2 + \frac{1+k}{Z}\frac{\partial \lambda}{\partial N_b}}\right\} + \frac{1+k}{Z}\frac{\partial^2 \lambda}{\partial N_l \partial \hat{N}_b}[U_l - U_b]}{2\left[1 - \frac{1+k}{Z}\frac{\partial \lambda}{\partial N_l}\frac{1}{2 + \frac{1+k}{Z}\frac{\partial \lambda}{\partial N_b}}\right]} \tag{6}$$

With the function $\lambda = F(\hat{N}_b, \hat{N}_l, N_b, N_l) + G(s)$, we have $\frac{\partial^2 \lambda}{\partial N_b \partial \hat{N}_b} = 0$ According to (6),

$$\frac{\partial N_l}{\partial \hat{N}_b} = \frac{1}{Z}\frac{\partial U_l}{\partial \hat{N}_b} = \frac{\alpha(s) + \left\{\frac{(1+k)\frac{\partial \lambda}{\partial \hat{N}_b}\left(2 + \frac{1+k}{Z}\left(\frac{\partial \lambda}{\partial N_b} + \frac{\partial \lambda}{\partial N_l}\right)\right)}{2 + \frac{1+k}{Z}\frac{\partial \lambda}{\partial N_b}}\right\} + \frac{1+k}{Z}\frac{\partial^2 \lambda}{\partial N_l \partial \hat{N}_b}[U_l - U_b]}{2Z\left[1 - \frac{1+k}{Z}\frac{\partial \lambda}{\partial N_l}\frac{1}{2 + \frac{1+k}{Z}\frac{\partial \lambda}{\partial N_b}}\right]} \tag{7}$$

Given $\alpha(H) = \alpha(L)$ and that the remaining terms in (7) are independent of s due to the additive separability of λ, we have We therefore conclude $\left.\frac{\partial N_l}{\partial \hat{N}_b}\right|_{s=H} = \left.\frac{\partial N_l}{\partial \hat{N}_b}\right|_{s=L}$.

Next, we derive $\frac{\partial U_b}{\partial \hat{N}_l}$. From Equation (3), we have:

$$\begin{aligned}\frac{\partial U_b}{\partial \hat{N}_l} &= \beta - \frac{\partial \lambda}{\partial \hat{N}_l}(1+k) - \frac{\partial P_b}{\partial \hat{N}_l} \\ &= \beta - \frac{\partial \lambda}{\partial \hat{N}_l}(1+k) - \left(\frac{\partial U_b}{\partial \hat{N}_l} + \frac{1+k}{Z}\frac{\partial \lambda}{\partial N_b}(\frac{\partial U_b}{\partial \hat{N}_l} - \frac{\partial U_l}{\partial \hat{N}_l}) + \frac{1+k}{Z}\frac{\partial^2 \lambda}{\partial N_b \partial \hat{N}_l}[U_b - U_l]\right)\end{aligned}$$

To get the

$$\frac{\partial U_b}{\partial \hat{N}_l} = \frac{\beta - (1+k)\frac{\partial \lambda}{\partial \hat{N}_l} + \frac{1+k}{Z}\frac{\partial \lambda}{\partial N_b}\frac{\partial U_l}{\partial \hat{N}_l} - \frac{1+k}{Z}\frac{\partial^2 \lambda}{\partial N_b \partial \hat{N}_l}[U_b - U_l]}{2 + \frac{1+k}{Z}\frac{\partial \lambda}{\partial N_b}} \tag{8}$$

From equation (2) we could get

$$\frac{\partial U_l}{\partial \hat{N}_l} = \frac{(1+k)\frac{\partial \lambda}{\partial \hat{N}_l} - \frac{1+k}{Z}\frac{\partial \lambda}{\partial N_l}\frac{\partial U_b}{\partial \hat{N}_l} - \frac{1+k}{Z}\frac{\partial^2 \lambda}{\partial N_l \partial \hat{N}_l}[U_b - U_l]}{2 - \frac{1+k}{Z}\frac{\partial \lambda}{\partial N_l}} \tag{9}$$

Substitute (9) into (8), we have,

$$\frac{\partial U_b}{\partial \hat{N}_l} = \frac{\beta - (1+k)\frac{\partial \lambda}{\partial \hat{N}_l} + \frac{1+k}{Z}\frac{\partial \lambda}{\partial N_b}\left[\frac{(1+k)\frac{\partial \lambda}{\partial \hat{N}_l} - \frac{1+k}{Z}\frac{\partial \lambda}{\partial N_l}\frac{\partial U_b}{\partial \hat{N}_l} - \frac{1+k}{Z}\frac{\partial^2 \lambda}{\partial N_l \partial \hat{N}_l}[U_b - U_l]}{2 - \frac{1+k}{Z}\frac{\partial \lambda}{\partial N_l}}\right] - \frac{1+k}{Z}\frac{\partial^2 \lambda}{\partial N_b \partial \hat{N}_l}[U_b - U_l]}{2 + \frac{1+k}{Z}\frac{\partial \lambda}{\partial N_b}}$$

simplify, and finally we have,

$$\frac{\partial U_b}{\partial \hat{N}_l} = \frac{\beta - \frac{(1+k)\frac{\partial \lambda}{\partial \hat{N}_l}\left[2 - \frac{(1+k)}{Z}\left(\frac{\partial \lambda}{\partial N_l} + \frac{\partial \lambda}{\partial N_b}\right)\right] + \frac{(1+k)^2}{Z^2}\frac{\partial \lambda}{\partial N_b}\frac{\partial^2 \lambda}{\partial N_l \partial \hat{N}_l}[U_b - U_l]}{2 - \frac{1+k}{Z}\frac{\partial \lambda}{\partial N_l}} - \frac{1+k}{Z}\frac{\partial^2 \lambda}{\partial N_b \partial \hat{N}_l}[U_b - U_l]}{2\left[1 + \frac{\frac{1+k}{Z}\frac{\partial \lambda}{\partial N_b}}{2 - \frac{1+k}{Z}\frac{\partial \lambda}{\partial N_l}}\right]} \tag{10}$$

With the function $\lambda = F(\hat{N}_b, \hat{N}_l, N_b, N_l) + G(s)$, we have $\frac{\partial^2 \lambda}{\partial N_l \partial \hat{N}_l} = 0$ And according to (10),

$$\frac{\partial N_b}{\partial \hat{N}_l} = \frac{1}{Z}\frac{\partial U_b}{\partial \hat{N}_l} = \frac{\beta(s) - \dfrac{(1+k)\dfrac{\partial \lambda}{\partial \hat{N}_l}\left[2 - \dfrac{(1+k)}{Z}\left(\dfrac{\partial \lambda}{\partial N_l} + \dfrac{\partial \lambda}{\partial N_b}\right)\right]}{2 - \dfrac{1+k}{Z}\dfrac{\partial \lambda}{\partial N_l}} - \dfrac{1+k}{Z}\dfrac{\partial^2 \lambda}{\partial N_b \partial \hat{N}_l}[U_b - U_l]}{2Z\left[1 + \dfrac{\dfrac{1+k}{Z}\dfrac{\partial \lambda}{\partial N_b}}{2 - \dfrac{1+k}{Z}\dfrac{\partial \lambda}{\partial N_l}}\right]} \tag{11}$$

Given $\beta(H) > \beta(L)$ and that the remaining terms in (7) are independent of s due to the additive separability of λ, we have we will get $\left.\frac{\partial N_b}{\partial \hat{N}_l}\right|_{s=H} > \left.\frac{\partial N_b}{\partial \hat{N}_l}\right|_{s=L}$

The corollaries follow directly. □

Proof of Proposition 2.

Proof. From (6) and (10), and $\frac{\partial^2\lambda}{\partial N_b \partial \hat{N}_b} = 0, \frac{\partial^2\lambda}{\partial N_l \partial \hat{N}_l} = 0,$

we have $$\frac{\partial U_l}{\partial \hat{N}_b} = \frac{\alpha + \left\{ \frac{(1+k)\frac{\partial\lambda}{\partial \hat{N}_b}\left(2 + \frac{1+k}{Z}\left(\frac{\partial\lambda}{\partial N_b} + \frac{\partial\lambda}{\partial N_l}\right)\right)}{2 + \frac{1+k}{Z}\frac{\partial\lambda}{\partial N_b}} \right\} + \frac{1+k}{Z}\frac{\partial^2\lambda}{\partial N_l \partial \hat{N}_b}[U_l - U_b]}{2\left[1 - \frac{1+k}{Z}\frac{\partial\lambda}{\partial N_l}\frac{1}{2 + \frac{1+k}{Z}\frac{\partial\lambda}{\partial N_b}}\right]}$$

Because $\frac{(1+k)\frac{\partial\lambda}{\partial \hat{N}_b}\left(2 + \frac{1+k}{Z}\left(\frac{\partial\lambda}{\partial N_b} + \frac{\partial\lambda}{\partial N_l}\right)\right)}{2 + \frac{1+k}{Z}\frac{\partial\lambda}{\partial N_b}} > 0$, we have,

$$\frac{\partial U_l}{\partial \hat{N}_b} > \frac{\alpha + \frac{1+k}{Z}\frac{\partial^2\lambda}{\partial N_l \partial \hat{N}_b}[U_l - U_b]}{2}$$

Similarly, we have $$\frac{\partial U_b}{\partial \hat{N}_l} = \frac{\beta - \frac{(1+k)\frac{\partial\lambda}{\partial \hat{N}_l}\left[2 - \frac{(1+k)}{Z}\left(\frac{\partial\lambda}{\partial N_l} + \frac{\partial\lambda}{\partial N_b}\right)\right]}{2 - \frac{1+k}{Z}\frac{\partial\lambda}{\partial N_l}} - \frac{1+k}{Z}\frac{\partial^2\lambda}{\partial N_b \partial \hat{N}_l}[U_b - U_l]}{2\left[1 + \frac{\frac{1+k}{Z}\frac{\partial\lambda}{\partial N_b}}{2 - \frac{1+k}{Z}\frac{\partial\lambda}{\partial N_l}}\right]}$$

Because of the assumption $(\frac{\partial\lambda}{\partial N_l} + \frac{\partial\lambda}{\partial N_b}) < 2\frac{Z}{1+k}$, we have

$$\frac{\partial U_b}{\partial \hat{N}_l} < \frac{\beta - \frac{1+k}{Z}\frac{\partial^2\lambda}{\partial N_b \partial \hat{N}_l}[U_b - U_l]}{2}$$

We arrive at:

$$\frac{\partial U_l}{\partial \hat{N}_b} > \frac{\alpha + \frac{1+k}{Z}\frac{\partial^2\lambda}{\partial N_l \partial \hat{N}_b}[U_l - U_b]}{2} > \frac{\beta + \frac{1+k}{Z}\frac{\partial^2\lambda}{\partial N_b \partial \hat{N}_l}[U_l - U_b]}{2} > \frac{\partial U_b}{\partial \hat{N}_l} \tag{12}$$

□