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FINTECH PLATFORMS AND ASYMMETRIC NETWORK EFFECTS: THEORY AND EVIDENCE FROM MARKETPLACE LENDING

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ABSTRACT

We conceptually identify and empirically verify using marketplace lending data the features distinguishing FinTech platforms from non-financial platforms: (i) Long-term contracts introducing default risk at both the individual and platform levels; (ii) Lenders' investment diversification to mitigate individual default risk; (iii) Platform-level default risk leading to greater asymmetric user stickiness and rendering platform-level cross-side network effects (p-CNEs), a novel metric we introduce, crucial for adoption and market dynamics. We incorporate these features into a model of two-sided FinTech platform with potential failures and endogenous participation/fees. The model predicts lenders' single-homing, occasional lower fees for borrowers, asymmetric p-CNEs, and the predictive power of lenders' p-CNEs in forecasting platform failures. Marketplace lending in China empirically corroborate our model predictions in this dynamic industry characterized by entries, exits, and network externalities. Specifically, lenders' p-CNEs are empirically lower on declining or more established platforms compared to growing or new ones. Moreover, lenders' p-CNEs predict platforms' survival likelihood among others, even at very early stages. Our findings provide novel economic insights on multi-sided FinTech platforms for both practitioners and regulators.

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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 digital economy with the rise of giant platforms such as Alibaba and Amazon. Digital platforms have become one of the most actively researched areas in business economics over the past decades, and cross-side network effects (CNEs)—the influence of the activities of players on one side of a platform on the players on the other—have long been recognized as a key driver of platform pricing and competition (e.g., Katz and Shapiro, 1994; Rochet and Tirole, 2003; Ellison and Ellison, 2005; Dubé, Hitsch, and Chintagunta, 2010).[1]

Nevertheless, existing theories typically leave out the possibility of platform failure, and empirical studies rely on data from one or two growing platforms without exploring systematic patterns across a large cross-section. More fundamentally, despite recent studies on lending marketplaces and crowdfunding sites, as well as frequent media discussions of mass platform failures and macroeconomic environments, little is understood about the distinguishing features of FinTech platforms and their interaction with CNEs, user adoption and fees, and platform evolution. On FinTech platforms, user participation not only influences individual user decisions but also plays a critical role in the platform's overall survival, making platform-level CNEs equally, if not more, important than the individual CNEs typically studied in the literature.[2]

To this end, we conceptually identify how FinTech platforms differ from non-financial platforms for the first time in the literature, with empirical support from a novel dataset of 988 Chinese marketplace lending platforms. Unlike Amazon or Uber that feature mostly spot transactions, financial platforms entail longer-term contracts

[1] For instance, a platform may sacrifice profits on one side to build the installed base and make the ecosystem more appealing on the other side (Hagiu, 2006; Parker and Van Alstyne, 2005; Weyl, 2010).

[2] Individual cross-side network effects (CNEs) refer to the impact of the user base on one side of a platform on the decision-making or utility of individual participants on the other side. For example, the utility of a lender joining a platform is influenced by the number of borrowers already present on the platform, and vice versa. This concept has been widely studied in the literature (e.g., Katz and Shapiro, 1994; Rochet and Tirole, 2003) and typically focuses on the micro-level interactions between users rather than aggregate platform dynamics.

and time transformation of money, which is the first distinguishing feature of fintech platforms and introduces default risk at both the transaction and the platform levels.

The individual default risk has both an idiosyncratic component and a systematic component. Unlike non-financial platforms, where products are typically indivisible, FinTech platforms allow for divisible investments, enabling lenders to mitigate idiosyncratic risks through diversification—the second distinguishing feature.

Third, the platform default risk leads to stronger asymmetric stickiness among users on FinTech platforms. Borrowers, as recipients of funds, are less concerned with platform failures since they benefit from not being pursued for repayment when a platform collapses. In contrast, lenders, as providers of funds, face greater concerns—not only about diversifying borrowers' delinquency risks but also about potential losses stemming from platform failures. Furthermore, incumbent borrowers typically build reputation or social connections on current platforms (Burtch, Ghose, and Wattal, 2014). In the absence of a well-established credit rating or reference system in marketplace lending markets, credit systems for borrowers are typically proprietary, making it hard for them to leave. On the other hand, lenders, due to the fungibility of money, do not need to build a reputation on a platform and can exit more easily. Using large-sample analysis and the event study method, we empirically verify that borrowers are stickier than lenders on marketplace lending platforms.

We incorporate these distinguishing features of financial platforms and platform failure into an otherwise canonical model of two-sided platforms (e.g., Armstrong, 2006; Rochet and Tirole, 2003, 2006; Belleflamme and Peitz, 2019). We define the elasticity of a borrower's (lender's) response to changes in the number of lenders (borrowers) as the lender's (borrower's) p-CNE. Our model shows that borrowers' stickiness results in low elasticity to the departure of lenders, leading to a low lender's p-CNE under adverse market conditions (such as when the platform is failing or shrinking). The asymmetries in lenders' p-CNEs across different stages further reveal that lenders' p-CNE serves as a predictor of unobservable sentiment toward financial platforms or the future market environment. In other words, lender's p-CNE forecasts platform's failure. The model also predicts lenders' endogenous single-homing and derives conditions under which platforms charge the single-homing side (lenders) higher fees—an inversion of the competitive bottleneck.

To validate the above predictions, we first calculated the p-CNEs for lenders and borrowers across the 988 platforms. Our empirical analysis confirms the novel asymmetries in p-CNEs: lenders' p-CNEs are larger for platforms that are new or growing compared to those that are terminal or declining, and the gap between borrowers' and lenders' p-CNEs is wider for struggling or declining platforms. These asymmetries stem from a key feature of financial platforms: the reluctant departure of borrowers as recipients of funds. Next, we examine the role of lenders' p-CNEs in predicting platform failure and find corroborating evidence. Specifically, a one standard deviation increase in lender's p-CNE is associated with around 0.7% reduction in the probability of platform failure in the following month.

Based on these findings, we investigate early predictions of long-run survival for FinTech platforms. We find that the lenders' p-CNEs in the first year, along with average trading volume and average interest rate, can serve as robust early predictors of platforms' failure rates in the long run. In particular, one standard deviation increase in the first-year lender's p-CNE decreases the probability of platform failure by 7%. We also find that platforms with VC backing and those launched in provinces with higher financial regulatory expenditures have a lower likelihood of failure. Overall, initial characteristics of a platform, particularly lenders' p-CNEs, are crucial indicators of its long-term success, providing valuable insights for regulators and investors.

Our findings, especially asymmetric p-CNEs and borrower stickiness, augment the fundamental understanding of multi-sided financial platforms, with 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 disclose information about p-CNEs to guide retail investors in managing risks associated with platform failures.

We draw empirical evidence from marketplace lending in China as representative financial platforms for several reasons. 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 marketplace lending platforms were introduced between 2008 and 2018, with more than two-thirds having failed or being under serious stress by the end of 2018. 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 Chinese setting allows us to identify asymmetric network effects systematically for the first time without relying on one or two thriving platforms with idiosyncratic characteristics.

Our paper contributes to studies on multi-sided platforms. Rochet and Tirole (2003) highlight the prevalence of two-sided markets and the importance of price allocation in their seminal study. Subsequent research explores price dependence, the size of externalities, and multi-homing (Armstrong, 2006); price structures designed to "get both sides on board" (e.g., Rochet and Tirole, 2006); the impact of platform compatibility on sales and consumer welfare (e.g., Lee, 2013); and CNEs' role in exacerbating platform competition (Clements and Ohashi, 2005), influencing platform entry (Zhu and Iansiti, 2012), and shaping platform investment and product development strategies (Anderson, Parker, and Tan, 2014).

We contribute by identifying and modeling the distinguishing features of FinTech platforms, uncovering asymmetries in platform-level CNEs (p-CNEs) and their roles in platform evolution—an area that, as Chu and Manchanda (2016) point out, remains little understood—as well as the possibility of an inverted competitive bottleneck under certain conditions. We are the first to study the novel measure p-CNE on FinTech platforms and platform failures both theoretically and empirically.[3] We are

[3] Empirically, a large literature in economics and marketing establish the presence of large CNEs in tech industries and gaming (e.g., Gandal 1994; Basu, Mazumdar, and Raj, 2003; Gandal, Kende, and Rob, 2000; Clements and Ohashi 2005; Srinivasan and Venkatraman 2010; Gretz 2010). Importantly, studies measure CNEs in VCRs (Ohashi, 2003), video games (Shankar and Bayus, 2003), personal digital assistants and software (Nair, Chintagunta, and

also among the first to study the performance and dynamics of platforms using a large panel data. In particular, our analysis for declining platforms fills in the gap in the empirical literature in that prior studies focus on p-CNEs only for growing platforms whereas we examine p-CNEs for both booming and distressed platforms.

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 et al. (2015), Jagtiani and Lemieux (2017), and Allen, Peng, and Shan (2018) 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 (2016) identify adverse incentives in marketplace lending that shape crowdfunding structure and regulation; De Roure, Pelizzon, and Thakor (2022) find that lenders on marketplace lending platforms bottom fish when regulatory shocks disadvantage banks; Vallee and Zeng (2019) analyze the optimal information distribution for marketplace lending; Tang (2019a) finds that marketplace 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 et al. (2021), which studies whether government affiliation is a valid signal about platform quality in China. We contribute by conceptually clarifying the distinguishing features of FinTech platforms and analyzing asymmetric p-CNEs and their implications for market outcomes, such as pricing and user participation, both theoretically and through data from the most prominent market for FinTech lending in history.

Dubé, 2004), etc. Our measurement follows the approach of Miao (2018) to measure the p-CNEs, which is closely related to the literature such as Chu and Manchanda (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. This method of calculating CNE through bilateral user elasticity differs from the individual CNE typically discussed in traditional theoretical models. We define it as a platform-level CNE and measure it using a large panel of financial platforms.

More broadly, our paper relates to the fast-growing literature on FinTech and crowdfunding platforms. For example, Belleflamme, Lambert, and Schwienbacher (2019) use data from two competing reward-based crowdfunding platforms in France to analyze the interplay of social learning, (one-sided) network effects, and platforms' performance. Cong and Xiao (2024) study observational learning and all-or-nothing thresholds on crowdfunding platforms, with broad implications for information aggregation, project selection, and funding feasibility. More recently, Hong, Lu, and Pan (2024) document increased performance chasing and risk-taking by mutual fund investors and managers due to the intermediation of financial products on fintech platforms. Our paper extends this literature by analyzing how the distinguishing features of FinTech platforms shape platform dynamics and enrich our understanding of network effects and pricing mechanisms on multi-sided platforms.

The remainder of the paper proceeds as follows: Section 2 introduces the institutional background and data; Section 3 conceptually highlights the distinguishing features of FinTech platforms and provides empirical evidence; Section 4 develops a model of two-sided FinTech platforms with rich predictions; Section 5 tests these predictions in the Chinese marketplace lending setting; Section 6 further examines the p-CNE and platform failure; Section 7 concludes. The appendices contain further institutional details and proofs of lemmas and propositions.

2. Institutional Background and Data Description

2.1. FinTech Platforms Around the World

Over the past decades, FinTech platforms around the globe have witnessed phenomenal growth and encompassed a wide range of services and technologies. According to a report by BCG, approximately 26,000 FinTech companies operated globally in 2023, a significant increase from around 12,000 in 2019. Most of these companies are concentrated in North America, Europe, and Asia-Pacific, with Asia-Pacific projected to surpass the United States and become the world's largest FinTech market by 2030.[4] The global FinTech market, without counting cryptocurrencies and other Web3 applications, is still expected to reach $228.24 billion in 2024 and grow to $397.24 billion by 2029, with a CAGR of 11.72% during this period.[5]

FinTech platforms and services are often multi-sided, allowing two or more user groups to interact with one another, creating value through cross-side network effects. Prominent examples include marketplace lending and crowdfunding. The world's first marketplace lending platform, Zopa, was established in the UK in 2005, and over the following decade, the whole market experienced rapid growth in various other countries, including the United States and China. According to incomplete statistics by 2015, online marketplace lending in the United States had doubled every year since 2010.[6] Marketplace lending reduces the role of commercial banks as financial intermediaries, broadens access to financial services, and partially compensates for gaps in traditional financial support.[7] Similarly, crowdfunding originated in the 1970s in the United States. The world's first crowdfunding website, ArtistShare, was established in 2001, adopting a reward-based crowdfunding model aimed at musicians and their fans. In 2009, Kickstarter was founded, which became the most influential crowdfunding platform.[8] The crowdfunding industry, involving equity-based, reward-based, and even token-based (Initial Coin Offerings), has proliferated since then, covering almost all sectors including technology, gaming, and medicine.

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[4] The data is sourced from the BCG report, *"Fintech Projected to Become a $1.5 Trillion Industry by 2030,"* available at https://www.bcg.com/press/3may2023-fintech-1-5-trillion-industry-by-2030.

[5] The data is sourced from Mordor Intelligence, available at https://www.mordorintelligence.com/industry-reports/global-fintech-market.

[6] The data is sourced from Morgan Stanley, available at https://www.morganstanley.com/ideas/p2p-marketplace-lending.

[7] The significance of the consumer loan market is evident in its sheer size, with $5 trillion of outstanding credit in 2023 (*Small Business Credit Survey, 2023*; *G.19 Consumer Credit Data, Federal Reserve Board*). Efficient capital allocation to consumer and small business sectors is vital for sustaining a dynamic and growing economy. Yet, traditional financial systems often ration out these loan applicants due to perceived creditworthiness risks. In this gap, FinTech lenders have risen to become major providers of capital to small businesses (see, for example, Tang 2019a; Vallee and Zeng, 2019; Gopal and Schnabl, 2022; Erel and Liebersohn, 2022; De Roure, Pelizzon, and Thakor, 2022). In recent years, marketplace lending platforms have gradually faced challenges under regulatory pressure and influence from monetary policies. Despite the ban of marketplace lending in its once largest market in China, blockchain-based DeFi (decentralized finance) lending has gained popularity. This evolution reflects the irreplaceable role of marketplace lending platforms in meeting unmet credit needs and fostering innovation in financial intermediation globally.

[8] As of August 16, 2024, the platform has successfully funded 264,311 projects, channeling a total of $8.21 billion into creative endeavors, with over 97 million pledges recorded. More information is available at https://www.kickstarter.com/.

Unlike BigTech credit, where platforms themselves provide funding (Frost et al., 2019; Bian, Cong, and Ji, 2023; Chen et al., 2024), marketplace lending and other types of crowdfunding as a dominant form of FinTech platforms feature at least two groups of decentralized users: investors/fund-contributors and entrepreneurs/fundraisers, with relatively open entry and no single entity wielding excessive market power in either group.[9] Moreover, contracts and transactions on FinTech platforms involve non-trivial durations and default risks at both the loan and platform levels, distinguishing them from non-financial platforms like Amazon.[10] Finally, like other multi-sided platforms, FinTech platforms crucially depend on cross-side network effects to thrive, but the nascent, complex, and novel nature of their business models means that they are also more heavily influenced by other elements such as market sentiments and regulatory policy changes compared to platforms such as e-Bay or Amazon.

2.2. Marketplace Lending in China

Marketplace lending was first introduced in China in 2007. While having a later start than the United States and United Kingdom, the Chinese marketplace lending has enjoyed phenomenal growth over one decade with more than 6,000 platforms having been introduced by 2018. In 2018 alone, 19 million investors and 13 million borrowers in China participated in marketplace lending and the transaction volume amounted to US $178.89 billion, as compared to US $8.21 billion in the United States. However, tightened regulations and cracking down on fraudulent platforms started in June 2018 and the number of platforms dropped by more than 50 percent to 1,021 by

[9] Even though Lending Club has switched from retail to institutional investors, there are multiple banks and institutions involved as fund contributors; it is not one Neobank and BigTech lending.

[10] Default risk on fintech platforms is much more prevalent than on other types of platforms. In 2018, China's marketplace lending industry experienced a severe wave of collapses. According to data from iiMedia Research, over 850 marketplace lending platforms ceased operations or encountered problems that year, with over 800 billion yuan in capital involved and more than 15 million users affected. Similar situations have occurred in the United States as well. For example, Lending Club experienced a default rate of over 10% between 2007 and 2011, with 5,161 out of 42,535 total loan records defaulting. Crowdfunding platforms have also seen defaults. For instance, according to incomplete statistics, as of early 2021, the crowdfunding platform Fifth Creation, established in March 2015, had 32 projects with abnormal dividends and buybacks, involving over 2.1 billion yuan in crowdfunding.

the end of 2018.[11] In January 2021, the State Council Information Office announced that all marketplace lending platforms are banned in China, citing financial stability risks. A thorough investigation into what was once the largest marketplace lending market remains missing till this day.

The Chinese marketplace lending once accounted for approximately 60% of global transaction volume and had rich dynamics in terms of user base growth and decline. Unlike the large financial institutions that dominate marketplace platforms in the European and American markets, China's marketplace lending market is characterized by a large number of individual investors and small lending platforms. This unique market participant structure affects market competition, and analyzing these participants' behaviors helps in fully understanding market dynamics and investor behavior on fintech platforms. Equally interesting, marketplace lending in China has undergone a complete lifecycle, transitioning from rapid development to facing risk events and eventually shutting down completely—all against a backdrop of regulatory evolution, from an initial absence of regulation to later stringent oversight. Understanding the entire growth trajectory of the China market can provide valuable insights for risk management and regulation of other FinTech platforms globally.

Due to its vast market scale, platform diversity, and complete development trajectory, the Chinese market provides a richer and unique dataset that is particularly advantageous for studying market lending and, more broadly, all fintech platforms that connect fund contributors and fundraisers. We collect a comprehensive dataset covering 988 marketplace lending platforms in China up to mid-2018. This dataset includes time series data from each platform's inception, capturing detailed information on bilateral user dynamics (both lenders and borrowers), the number of loans and investments, transaction volumes, interest rates, and more. These variables offer a depth and breadth of information that is rarely available in other markets, making the Chinese context exceptionally valuable for studying the intricacies of

[11] The data is sourced from a Bloomberg article titled *"China's Online Lending Crackdown May See 70% of Businesses Close,"* available at https://www.bloomberg.com/news/articles/2019-01-02/china-s-online-lending-crackdown-may-see-70-of-businesses-close.

FinTech platforms. The insights gained from analyzing this market offer significant implications for understanding and anticipating future global FinTech trends.

2.3 Data

In our empirical analyses, we collect data from Zero One Finance, a private data vendor specializing in marketplace lending. The dataset covers transactions on 1,404 marketplace lending platforms at a weekly frequency from June 26, 2007, to June 30, 2018.[12]

We exclude marketplace lending platforms deemed fraudulent by Chinese courts because our main empirical exercises focus on general economic mechanisms and testing predictions of a model that does not account for fraud activities or Ponzi schemes.[13] We also remove platforms with a lifespan of less than one year since our CNE metric requires at least one year of observations. Overall, our final dataset includes 988 platforms with 141,322 weekly observations. These platforms are broadly representative of the industry, accounting for 68% of the marketplace lending market's total trading volume in 2017, for example.[14]

Our data contains the starting (and closure) date(s) of platforms and their transaction data. Panel A of Table 1 presents the distribution of platform inception years: only 13 platforms were established before 2012, followed by several years of rapid growth and a notable decline starting in 2015. Of the 988 platforms in our dataset, 418 (42%) had failed by June 2018. The average lifespan of failed platforms is approximately 2.2 years, compared to 3.5 years for surviving platforms. As shown in

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[12] The earliest marketplace lending platform in China is PaiPaiDai, which started in 2007. Since then, the number of marketplace lending platforms started to increase rapidly, the years of 2014 and 2015 saw a strong increase in numbers of marketplace lending 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 marketplace lending platforms (https://www.caixinglobal.com/2018-07-10/china-vows-continued-tight-grip-on-internet-finance-101297647.html). As we study the p-CNEs, which are CNEs from a market perspective, we exclude the sample after June 2018.

[13] These 57 platforms, deemed fraudulent by Chinese courts and excluded from the main analysis, constitute only 4% of the sample. Notably, the results of pure predictive tests remain robust even when these platforms are included.

[14] Note that, our data covers 1.91 trillion yuan of trading volume, while the total trading volume of Chinese marketplace lending market is 2.80 trillion yuan.

Figure 1, the survival rate, estimated using the Kaplan-Meier method, declines steadily, stabilizing around 40% after 4 years.

The transaction data include weekly observations such as the number of investments made by lenders, the number of loans taken by borrowers, trading volume (in units 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. Note that on each platform the number of loans (investments) does not necessarily equal the numbers of borrowers (lenders) because a borrower may apply for multiple loans for different projects and a lender may allocate investment over multiple borrowers and multiple loans.

Panel B of Table 1 reports the mean and standard deviation of all variables. The number of investments on live platforms is about four times higher than on failed platforms (row 2), while the number of loans is about three times higher (row 3). The average loan and investment sizes are 58% and 21% larger, respectively, for live platforms compared to failed ones (rows 7 and 8). The number of loans per borrower and investments per lender are also higher on live platforms, by 72% and 120%, respectively (rows 9 and 10). Additionally, the borrowing amount per borrower is 60% higher for live platforms relative to failed ones (row 11), while the investing amount per lender is 40% higher for live platforms (row 12). Overall, both borrowers and lenders are more active on live platforms than on failed ones. The average interest rates for live and failed platforms are 11.7% and 16.1%, respectively (row 6). The origination time for loans on platforms that remain operational is only 22.2% ($exp(8.951 - 10.455)$) of that on platforms that eventually failed (row 13).

In addition, we also manually collect information about the platforms from www.wdzj.com—the largest ever information aggregator of marketplace lending in China, which has stopped operating now—about whether the platform is owned or funded by a State-owned Enterprise (SOE), the headquarter city of the platform, and the corresponding GDP and population data from the National Bureau of Statistics of China.

3. Distinguishing Features of FinTech Platforms: Concepts and Empirics

3.1. What Makes FinTech Platforms Special?

Non-financial platforms mostly feature spot transactions completed in a short time (e.g., the purchase of a book on Amazon or short-term rentals on Airbnb). In contrast, FinTech platforms often entail the transfer of money across time and contracts that often last for a significant duration, making default risk a critical concern. On such financial platforms, investors are analogous to buyers on non-financial platforms, as both provide homogeneous goods, i.e., money, in exchange for non-homogeneous goods, i.e., a claim on some cash flows of funded individuals/projects or goods for consumption, respectively. However, investors face risks of default originating from both individuals raising finance (e.g., when a borrower's project fails) on the platform and the platform itself. The fundraisers, on the other hand, face relatively lower risks from platform failure and may even benefit, as they no longer need to repay investors if the platform fails.[15]

The platform-level default risk inherent in long-term contracts leads to a stronger asymmetric stickiness between the two sides of FinTech platforms—the second distinguishing feature. Some degrees of asymmetric stickiness do exist on non-financial platforms. For example, sellers often incur high costs onboarding (such as setting up a store, building a reputation, etc.), which makes them less willing or prompt to leave a platform than buyers based on the simple argument of real option exercise. Similarly, on FinTech platforms, individuals and entrepreneurs raising financing are less likely to leave even when counterparties decrease, because leaving a platform often results in the loss of the credit and reputation built (Burtch, Ghose, and Wattal, 2014). However, FinTech platforms would feature even stronger

[15] On non-financial platforms, such as e-commerce platforms, buyers generally do not face individual default risk. Buyers may return items or file false claims about shipping or item quality, and most platforms accommodate such requests in short period of time. When a platform fails, sellers might incur losses on orders that have been shipped but not yet paid for, and buyers might lose payments for undelivered goods. However, since payments are often held in escrow by third-party services until transactions are completed, users can seek recourse through these payment services if the platform collapses.

asymmetric stickiness, especially in bad times precisely because the impacts of platform default on fundraisers and financiers differ. When a platform fails, financiers face significant challenges in recovering their investments, while fundraisers benefit from the relief of not having to repay the principal. As a result, during times of crisis, fundraisers tend to be more "sticky" than financiers.

In addition to platform-level default risk, long-term contracts also introduce individual default risk, which incentivizes lenders to diversify their investments across multiple projects or borrowers on a platform. This makes the divisibility of investments the third distinguishing feature of FinTech platforms. Unlike non-financial platforms, such as e-commerce, where transactions are generally indivisible—buyers typically purchase items for unit consumption—FinTech platforms allow for the division of investments, enabling lenders to mitigate idiosyncratic risks. This risk mitigation strategy naturally leads to investment diversification.[16]

Among the three distinguishing features discussed, platform default risk that amplifies the asymmetric stickiness between fundraisers and financiers is the central focus of this study. Fundraisers' stickiness benefits the platform ex-post, as it helps mitigate the large exodus of financiers during significant negative shocks by maintaining their presence on the platform and sustaining cross-side network effects. Although the above conceptual insights apply to many FinTech platforms, marketplace lending is a dominant form of FinTech platform and thus our focus. As such, we use "borrowers" and "lenders" interchangeably and often in place of "entrepreneurs/fundraisers" and "investors/financiers," respectively. We next use our data from marketplace lending to empirically verify the asymmetric stickiness of FinTech platforms.

3.2. Empirical Evidence of Asymmetric Risk and Stickiness

The asymmetric stickiness between borrowers and lenders refers to the tendency for lenders to exit more than borrowers during periods of platform decline. We

[16] In Appendix Table B1, we present evidence supporting lenders' diversification on the same platform. The results show that as the number of borrowers on a platform increases, the average number of investments per lender rises, while the average amount per investment declines.

conduct direct tests to examine the differing levels of stickiness between borrowers and lenders using multiple methodologies.

3.2.1. Large-sample Analysis of Departures Preceding Platform Failures

First, we examine the relative number of lenders to borrowers over time. Figure 2 shows the average ratio of the cumulative number of lenders from week t-3 to week t to the number of borrowers across all failed platforms throughout their entire life cycles. Considering the different lifespans of various platforms, we standardized all lifespans to a range of 0 to 100 and calculated the average relative number. To mitigate the influence of outliers, we excluded data points beyond the 99th or 95th percentile before taking the average. From Figure 2, we observe that during the first third of their lifespan, the relative number of lenders to borrowers remains stable at about 12.5 under the 95th percentile threshold (15 under the 99th percentile threshold). After that, the relative ratio gradually declines, dropping to 10 with the 95th percentile threshold (above 12 with the 99th percentile threshold). The declining ratio indicates that, prior to platform failure, lenders are leaving at a higher rate than borrowers.

Next, we examine the departure rate of the borrowers and the lenders 6 months before a platform failure directly. 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 2 reports the change in 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 a platform's failure, we then take the difference to its previous month.

Panel A of Table 2 shows that borrowers leave more slowly than lenders every month before platform failure. On average, the monthly difference in log number changes between borrowers and lenders is 3% (t-statistics 3.75), 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 2, we also report the change in log numbers of borrowers and lenders up to 6 months after a platform's birth. We cannot find a consistent pattern that borrowers enter faster or slower than the lenders, and the overall entry rate difference between borrowers and lenders is small and insignificant.

Note that the average departure rate (9.9%) for lenders during the half-year before the platform failure is much larger than the lenders' entry 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 staying on a failing platform. In contrast, the departure and entry rates during the half-year before the failure and the half-year after the birth are rather similar (6.9% v.s. 4.7%), which reaffirms that borrowers are less motivated to leave the platform.

3.2.2. The Ezubao Fraud Event

To further test the asymmetric stickiness, we use the difference-in-difference (DID) method to examine how borrowers and lenders behave differently when a negative shock occurs. Ezubao, once the largest marketplace lending 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.[17] The Ezubao scam was a significant shock to the Chinese marketplace lending industry. Many borrowers and lenders contemplate leaving marketplace lending platforms after realizing they could be victims of similar scams. We use the Ezubao incident as an exogenous shock to examine the borrowers' and lenders' stickiness.

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

$$lnN_{i,t}^{player} = d_0 + d_1 dummy1 + d_2 dummy2 + d_3 dummy1 \times dummy2 + d_4 lnV_{i,t} + d_5 I_{i,t} + d_6 lnLS_{i,t} + d_7 lnIA_{i,t} + Platform + u_{i,t}, \quad (1)$$

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

where $N_{i,t}^{player}$ is the number of borrowers or lenders at the week t 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. The coefficient for the difference-in-difference effect, d_3, therefore presents the difference in the departure rates between borrowers and lenders. Control variables are $lnV_{i,t}$, $I_{i,t}$, $lnLS_{i,t}$ and $lnIA_{i,t}$ representing interest rates, log loan size per loan and log investing amount per lender in week t on platform i, respectively. And $Platform$ refers to platform fixed effect.

Table 3 shows a positive coefficient of the difference-in-difference item (d_3) with a 5% significance level. Columns (1) and (2) present the results of equation (1), showing that facing the Ezubao scam, the staying population for borrowers is 4.7% more than that of lenders on average. To ensure robustness, we include time fixed effects in columns (3) and (4), and the results remain unchanged.

Overall, through two different types of shocks (platform failures/declines and the Ezubao event), we have shown that borrowers are more reluctant to leave compared to lenders, i.e., borrowers exhibit stronger stickiness and therefore stay for longer.

4. A Model of Two-sided FinTech Platforms with Potential Failures

With the aforementioned distinguishing features well-established conceptually and empirically, we build a model of two-sided FinTech platforms with platform failures. We illustrate how the characteristics of financial platforms influence p-CNE and identify the key factors driving platform dynamics and survival/failure.

4.1 A Baseline of Monopoly Platform

We start with a single platform, a continuum of lenders, and a continuum of borrowers, with both lenders and borrowers being of unit measure. For simplicity, lenders can each lend a unit amount; each borrower borrows the same amount $Q > 1$, consistent with the fact that empirically the number of lenders or investments is bigger than the number of borrowers or loans. Agents interact in several stages: First, given a platform's installed base, its owner sets fees. Then potential lenders and borrowers simultaneously decide whether to participate. The platform owner collects fees (P_l, P_b) from participants 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 the equilibrium numbers of borrowers and lenders. Let R be a uniform interest rate that is endogenous to the model.[18] Let $\lambda(s)$ denote a platform's survival probability by the end of the interaction, which is a function of exogenous variables and in particular is increasing in s, a state variable holistically capturing government policies, systematic shocks to projects' feasibility, investor sentiment, platform age, userbase trend, etc. Importantly, s can only be imperfectly forecasted when agents make decisions. For simplicity, suppose s is either H (optimistic) or L (pessimistic). Note that lenders' investments can be divided across multiple loans on the same platform, thereby diversifying individual default risk.[19] Therefore, our model focuses on platform-level default risk.

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

$$\begin{aligned} U_l &= \alpha(s)\widehat{N}_b + \lambda R - (1-\lambda) - P_l = \alpha(s)\widehat{N}_b + \lambda(1+R) - 1 - P_l, \\ U_b &= \beta(s)\widehat{N}_l - \lambda RQ + (1-\lambda)Q - P_b = \beta(s)\widehat{N}_l - \lambda(1+R)Q + Q - P_b, \end{aligned} \tag{2}$$

where $\beta(s) > 0$ measures the benefit a borrower enjoys from interacting with each lender in the installed base and $\alpha(s) > 0$ measures the benefit a lender enjoys from interacting with each borrower in the installed base. Lenders and borrowers will choose to participate in a marketplace platform when $U_l \geq v_l$ and $U_b \geq v_b$, where v_l and v_b are lenders' and borrowers' outside option values, respectively, each uniformly distributed within $U[0, Z]$.

[18] R is determined by the demand and supply of funding capital on the platform and we allow it to differ across platforms when we introduce platform competition.

[19] This is the third distinguishing feature of Fintech platforms.

The fact the utilities depend on the installed base can be interpreted as new borrowers deciding whether to join the platform and search for funding based on the presence of installed lenders (who are known to be on the platform). Similarly, new lenders decide whether to invest on the platform by looking at projects posted by (installed) existing borrowers. While CNEs from an individual perspective typically correspond to $\alpha(s)$ and $\beta(s)$ in the literature (Armstrong, 2006; Armstrong and Wright, 2006), we introduce a novel and natural CNE concept at the platform level, p-CNE, using the elasticity of the two-sided users. P-CNE captures how changes in the number of users on one side lead to changes in the number of users on the other side in aggregate, which affects platform outcomes. In our model, the lenders' p-CNE (CNE_l) can be represented by $\frac{\partial N_b}{\partial \hat{N}_l} \cdot \frac{\hat{N}_l}{N_b}$, and the borrowers' p-CNE (CNE_b) can be represented by $\frac{\partial N_l}{\partial \hat{N}_b} \cdot \frac{\hat{N}_b}{N_l}$.

We set $\beta(H) = \beta$ and $\beta(L) = (1-c)\beta$, where $c \in (0,1)$. In Section 3, we have shown that on a financial platform, the stickiness of borrowers and lenders is asymmetric (the second distinguishing feature of Fintech platforms). When $s = L$, the platform's survival probability decreases, leading to a decline in U_l for lenders. Consequently, existing lenders are motivated to leave the platform easily, reducing the installed base benefit for potential borrowers. In contrast to lenders, borrowers benefit from the platform's failure and therefore have no incentive to leave the platform during an adversarial market $(s = L)$ environment. As such, $\alpha(H) = \alpha(L) = \alpha$.

The users' participation functions are given by,

$$N_b = \frac{1}{Z} U_b \text{ and } N_l = \frac{1}{Z} U_l, \tag{3}$$

where N_b and N_l are the number of borrowers and lenders in equilibrium. The loan market's clearing condition is simply, $N_l = N_b Q$, which greatly simplifies the solution.

The platform owner's expected profit is,

$$\pi(P_l, P_b) = N_l(P_l - f_l) + N_b(P_b - f_b), \tag{4}$$

where f_b and f_l are the service costs per borrower and per lender. We allow the platform owner to maximize profit over the fees (P_l, P_b) she sets, which essentially varies the utilities lenders and borrowers get. Without loss of generality, we normalize f_b and f_l to be zero.

Proposition 1. *Lenders' p-CNE is increasing in s while borrowers' p-CNE is decreasing in s.*

This proposition implies that during the first year of a platform's launch or when the user base is increasing (situations in which it is more likely $s = H$), lenders' p-CNE is higher than that during the year leading to a platform's demise or when the user base is decreasing (situations in which it is more likely $s = L$). Conversely, borrowers' p-CNE exhibits the opposite pattern. This effect is rare on non-financial platforms because failures on non-financial platforms affect both sides of the market to similar extents, whereas on financial platforms, failures during the contracts are a boon to borrowers who no longer need to repay.

Note that for non-financial platforms, $\beta(L)$ would not be significantly smaller, as the buyer (money provider) can return a good with false claims immediately due to 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 (sellers) from unfairly taking advantage of the sellers' (buyers') or platforms' return policies. But for financial platforms, due to the non-trivial duration of the contracts, if sellers (fundraisers) do not pay back after the platform's collapse, it is typically difficult for the platform to assist in recovering the lender's principal.

Now it should be clear that the p-CNE asymmetries can be largely attributed to the unique features of financial platforms. We thus 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.

Because s is not directly observed until the end of the period and $\lambda(s)$ is increasing in s, the value of lenders' p-CNE and borrower's p-CNE reveal incremental information about s due to their correlation, which is useful in predicting the platform's survival.

Are the outcomes socially efficient? In Appendix C, we consider a social planner's solution. Intuitively, the platform owners' profit maximizing fees distort participation.

Proposition 2. *Relative to the social optimum, platform fees are inefficiently high, leading to under-participation by agents.*

4.2 Competition Among Marketplace Platforms

We next examine competition among marketplace platforms in the presence of p-CNEs. Suppose there are two platforms, $i = A, B$, perceived as identical by borrowers and differentiated by lenders. Platform heterogeneity for lenders is captured using a Hotelling model, where the platforms occupy the two ends of a Hotelling line of a unit interval, with lenders uniformly distributed along the line. A lender located at x on the interval has a transportation cost of tx when participating in platform A and a transportation cost of $t(1-x)$ when participating in platform B. Both borrowers and lenders are permitted to join multiple platforms simultaneously.

Borrowers' participation. Borrowers can apply for loans on both platforms without additional costs, as loan documents are largely consistent across platforms, making the platforms identical to borrowers, thereby incurring no transportation costs. Since marketplace platforms typically do not require collateral, borrowers are not constrained by limited collateral when applying to new platforms. Furthermore, borrowers may benefit from platform failures, as in practice, most borrowers cease repaying their loans when a platform collapses, incentivizing them to borrow from multiple platforms**.** When borrowers decide whether to join a platform, their decision to join one platform is independent of their decision to join the other. As long as the utility of joining platform i exceeds the outside option, borrowers will choose to join platform i. The utility for a borrower joining platform i is,

$$U_b^i = \beta(s)\widehat{N}_l^i - \lambda^i\left(1 + R^i\right)Q + Q - P_b^i, \tag{5}$$

where λ^i is the survival probability of platform i, and R^i is the interest rate on platform i. Borrowers will choose to participate in a marketplace platform if $U_b^i \geq v_b$, where v_b is the outside option value for borrowers, uniformly distributed within $U[0, Z]$.

Lenders' participation. For lenders, they have preferences for different platforms. As described in Section 4.1, each lender lends the same amount of 1 unit. For a lender located at x, she can invest all 1 unit in platform i (where $i = A, B$), yielding a utility of,

$$\begin{aligned} U_l^A &= \alpha(s)\widehat{N}_b^A + \lambda^A(1 + R^A) - 1 - P_l^A - tx, \\ U_l^B &= \alpha(s)\widehat{N}_b^B + \lambda^B(1 + R^B) - 1 - P_l^B - t(1 - x). \end{aligned} \tag{6}$$

Here, x is the distance from the lender to platform A. We assume lenders' unit transport costs t and borrowers' maximum outside option value Z are sufficiently high to ensure that participation on both sides across two platforms remains positive in equilibrium. Lenders can also choose to invest k in platform A and $1 - k$ in platform B, where $k \in (0,1)$, indicating that lenders can multi-home. In this case, the utility of multi-homing is:

$$U_l^{A,B} = \alpha(s)\widehat{N}_b^{A,B} + k[\lambda^A(1 + R^A) - 1] + (1 - k)[\lambda^B(1 + R^B) - 1] - P_l^A - P_l^B - t. \tag{7}$$

$\widehat{N}_b^{A,B}$ is the total number of borrowers that a lender can connect with when multi-homing. However, lenders will choose to single-home, as detailed in Lemma 1.

Lemma 1. Lenders endogenously single-home.

Lemma 1 allows us to focus on the case where lenders single-home and borrowers multi-home. Following Armstrong (2006) and Belleflamme and Peitz (2019), we use the model containing two platforms, where lenders deal with a single platform (single-homing) and borrowers deal with both platforms (multi-homing). We define N_k^i as the equilibrium numbers of participants ($k = l, b$) on platform i. The number of lenders on the two marketplace platforms is given by the Hotelling specification,

$$N_l^A = \frac{1}{2} + \frac{U_l^A - U_l^B}{2t} \text{ and } N_l^B = \frac{1}{2} + \frac{U_l^B - U_l^A}{2t}. \tag{8}$$

Here, t represents the transportation costs for lenders. The number of borrowers is still given by,

$$N_b^A = \frac{1}{Z} U_b^A \text{ and } N_b^B = \frac{1}{Z} U_b^B, \tag{9}$$

same as equation (3) in Section 4.1. We still impose the loan market's clearing condition $N_l^i = N_b^i\, Q$.

The platform i's expected profit is,

$$\pi^i(P_l, P_b) = N_l^i\left(P_l^i - f_l\right) + N_b^i\left(P_b^i - f_b\right), \tag{10}$$

where f_b and f_l are the service costs per borrower and per lender, respectively, and are assumed to be identical across both platforms. Same as in equation (4), without loss of generality, we normalize f_b and f_l to be zero.

Proposition 3: *Platforms charge lower fees to lenders than to borrowers* $(P_l^i < P_b^i)$*, if and only if* $2Qt < Z$.

Here, t represents the unit transportation cost for lenders, and Z is the upper bound of the borrowers' outside option value. t reflects the "preference heterogeneity" or "cost" that lenders incur when choosing between different platforms, which in turn affects the level of competition between the platforms. When t is high, lenders are less likely to switch platforms due to higher switching costs. This gives the platform greater pricing power, allowing it to raise P_l to capture more profit. Conversely, when t is low, lenders become more flexible in their platform choices, making it easier for them to switch platforms. This increased competition between platforms forces them to lower P_l to attract lenders. The borrowers outside option Z influences the number of borrowers joining a platform, thereby affecting the interest rate in equilibrium. When Z increases, borrowers have more attractive alternatives outside the platform, leading to a decrease in loan demand and further lowering the platform's interest rate. A lower interest rate increases the platform's attractiveness to borrowers but decreases its appeal to lenders, then P_l decreases and P_b increases.[20]

[20] The detailed proof can be found in the proof of Proposition 3 in Appendix C.

Note that borrowers are multi-homing while lenders are single-homing, often leads to what is known as "competitive bottlenecks" in platform markets (Armstrong, 2006; Armstrong and Wright, 2006; Belleflamme and Peitz, 2019; Bakos and Halaburda, 2020). In the classic competitive bottlenecks model, platforms typically charge low fees or even subsidize the single-homing side (lenders in our model), while imposing higher fees on the multi-homing side (borrowers in our model). Belleflamme and Peitz (2019) argue that the multi-homing side does not always pay higher fees. Our model suggests that when competition for lenders is low (i.e. high t) or when borrowers' outside options are weak (i.e. low Z), fintech platforms may charge higher fees to the single-homing lenders, inversing the competitive bottleneck. In reality, the fee structures of marketplace lending platforms also align with the characteristics of competitive bottlenecks, but due to varying levels of competition and differences in borrowers' outside options, these fee structures exhibit notable differences across different countries.

In China, platform competition is intense, reducing *t* and causing fees charged to investors (lenders) to be low or even zero, as platforms compete aggressively to attract and retain lenders. Conversely, in the United States, less intense competition results in higher *t*, enabling platforms to charge lenders a positive P_l, as higher switching costs make lenders less sensitive to fees. Additionally, borrowers in the United States have stronger outside options (*Z*), giving platforms more space to charge a higher P_b without losing borrowers to alternative financing sources.[21]

Proposition 4. *Under platform competition, lenders' p-CNE remains increasing in* s*. However, the case of borrowers' p-CNE becomes ambiguous.*

[21] For instance, U.S.-based platform Lending Club charges borrowers a loan origination fee ranging from 1.11% to 5% and imposes a 1% service fee on lenders based on the total amount repaid. Similarly, another U.S. platform, Prosper, charges borrowers a management fee of 1% to 5% and applies a 1% annual management fee to investors. In contrast, China-based Paipaidai exempts lenders from transaction service fees, requiring borrowers to pay a fee of 2% to 4% of the loan principal, and offers a membership system providing lenders with benefits like interest-free vouchers and compensation for failed loans to attract lenders. These examples highlight the difference in fee structures between U.S. platforms, which charge both borrowers and lenders, and Chinese platforms, which primarily focus on borrower fees, reflecting more intense competition in the Chinese marketplace lending environment.

Proposition 4 explains that after the introduction of competition, lenders' p-CNE continues to maintain a positive relationship with the platform's state. However, under the influence of inter-platform competition, the relationship between borrowers' p-CNE and the platform's state becomes inconsistent, depending on the relative sizes of $\widehat{N}_l^A$ and $\widehat{N}_l^B$. If $\widehat{N}_l^i > \widehat{N}_l^{-i}$, then $\frac{\partial CNE_b^i}{\partial s} < 0$, which is consistent with the relationship between CNE_b and s in Proposition 1. Proposition 4 implies that under platform competition, only lenders' p-CNE remains an effective forecaster of platform survival or failure, whereas borrowers' p-CNE no longer serves this purpose.

4.3. Model Implications and Predictions

Based on our models, we develop hypotheses related to the relationship between lenders' and borrowers' p-CNEs and platform failure, demonstrating why p-CNE is important in predicting platform status. In Proposition 1, we show that lenders' p-CNEs are asymmetric in different states. In an adversarial market environment, lenders' p-CNEs are smaller than in a good state due to lower stickiness for lenders on a marketplace platform. Furthermore, Proposition 4 implies that lenders' p-CNEs consistently predict platform failure negatively in a competing market. Based on these propositions, we propose the following hypothesis:

Hypothesis 1: There is asymmetry in marketplace lending platform p-CNEs. Specifically, the lender's p-CNE varies across different stages of the platform's lifecycle, with the lender's p-CNE being higher in good states.

Hypothesis 2. Lenders' p-CNE can forecast the future status of a platform (larger lender's p-CNE is associated with lower platform failure probability), while borrowers' p-CNE cannot.

Hypothesis 1 clarifies the asymmetry of p-CNE in financial platforms, a crucial factor for these platforms. The asymmetry reveals that lenders' p-CNE is higher on growing platforms, suggesting that lenders' p-CNE could reliably predict platform survival. This implies a negative relationship between lenders' p-CNE and the probability of platform failure, leading to Hypothesis 2. Unlike lenders' p-CNE, in a monopoly platform, borrowers benefit from platform failure. In adverse market conditions, such as during the Ezubao crisis, borrowers tend to remain more committed, making borrowers' p-CNE a positive predictor of platform failure. However, in a competitive environment, the initial size of a competing platform can negatively impact the platform's growth. The "winner-takes-all" phenomenon in platform economics diminishes the potential increase in borrowers due to gains from platform failure, making borrowers' p-CNE insufficient to predict platform failure under competition.

5. Empirical Tests of Model Predictions

5.1 Measurement of Cross-side Network Effects at the Platform Level

We follow the empirical literature on two-sided platforms (e.g., Stremersch et al., 2007; Chu and Manchanda, 2016; Miao, 2018) to define lenders' p-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' p-CNE at time t+1 is the elasticity of the number of lenders' new investments at t+1 to the number of active borrowers in period t.

There are several confounding issues. 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 likely increases the investment opportunity for lenders, which increases the future credit available to borrowers, generating a serial dependence. Second, prior loan availability means more intense competition among borrowers, reducing the probability that borrowers get funded and discouraging them from borrowing. This "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.[22]

[22] 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.

Therefore, in measuring the p-CNEs we need to control serial dependence (or the same-side network effect) on the same side.

In addition to the prior number of loans and investments, following Miao (2018), we use the lagged one period variables of interest rates, average loan size per loan, and average investing amount per lender as control variables, recognizing that the dependent variables are equilibrium quantities determined by both supply and demand.[23] We run a weekly time-series regression over an annual window to measure the p-CNEs for both the borrowers and lenders:

$$lnN_{i,t+1}^{Inv} = b_0 + b_1 lnCN_{i,t}^{Borrower} + b_2 lnN_{i,t}^{Inv} + b_3 I_{i,t} + b_4 lnLS_{i,t} + b_5 lnIA_{i,t} + u_{i,t+1}, \quad (11)$$

$$lnN_{i,t+1}^{Loan} = c_0 + c_1 lnCN_{i,t}^{Lender} + c_2 lnN_{i,t}^{Loan} + c_3 I_{i,t} + c_4 lnLS_{i,t} + c_5 lnIA_{i,t} + u_{i,t+1}, \quad (12)$$

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 and most people receive salaries monthly. Hence, it is likely that borrowers raise funds at a monthly horizon.[24] b_1 is the borrowers' p-CNE, and c_1 is the lenders' p-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 per loan, and log investing amount per lender in the t^{th} week on the i^{th} platform, respectively.

Table 4 reports both borrowers' and lenders' p-CNEs for the live and failed platforms, respectively. The average p-CNEs of borrowers and lenders are 0.152 and 0.147 for failed platforms, and 0.146 and 0.191 for live platforms. Over 60% of p-CNEs are positive. The correlation between borrowers' and lenders' p-CNEs is 0.53 for failed platforms and 0.44 for live platforms.

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[23] 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.

[24] See the loan purpose of lending club (https://www.lendingclub.com), for example.

Because p-CNE is the elasticity of the number of trades on the one side to the number of opposite-side agents, 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. In Table 5, we group the p-CNEs according to the lifecycle of failed platforms into three categories: one year after the starting date (P1), the middle year (P2), and one year before failure (P3).[25] We then calculate the average borrowers' and lenders' p-CNEs in these three lifecycle stages.

For borrowers' p-CNEs, those observed during failing periods are larger than those during the initial periods, but the difference is statistically insignificant. In contrast, the lenders' p-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' p-CNEs for the take-off and failing periods is prominent with a magnitude of -0.08 (t-statistics of -2.3).

This reveals an *asymmetry* concerning lenders' p-CNEs, i.e. it is much smaller in the failure period than that in the take-off period. As the lenders' p-CNE refers to the borrowers' participation with the arrival or departure of a marginal lender, the asymmetric lenders' p-CNEs, thus, inform that borrowers are relatively stickier and do not leave as quickly from failing platforms. This finding supports Hypothesis 1.

5.2. Empirical Analysis of Asymmetric P-CNEs

Through the preliminary examination of failed platforms, we have identified an asymmetry in lenders' p-CNEs across different stages of the lifecycle. In this section, we employ regression analysis and data from all platforms to further investigate and robustly test Hypothesis 1. We find that lenders' p-CNEs depend on the expected status of a platform such as its lifecycle stage and trends. Note that this expected status is not always observable ex-ante and may only be 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

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

to be big tomorrow is stochastic but may be imperfectly predicted from today's scale if the platform scale exhibits persistence.

We use platform scale trends (the entry or departure of players over the trailing 12 months) as proxies for the status of a platform (growing vs. declining) and analyze their relationship to the platform's p-CNEs.[26] We take the trading volume as the proxy for the scale of a platform, and run the following panel regression:

$$PCNE_{i,t}^{Player} = d_0 + d_1 Negative(\Delta V_{i,t}) + d_2 lnV_{i,t} + d_3 I_{i,t} + d_4 lnLS_{i,t} + d_5 lnIA_{i,t} + Time + RelativeMonth + u_{i,t}, \tag{13}$$

where $player$ refers to either lender or borrower, $PCNE_{i,t}^{Player}$ represents the player's (lender's or borrower's) p-CNEs for the final week of month t on platform i, measured using a one-year rolling window. $\Delta V_{i,t}$ is the change in the trading volume over the past year, indicating trends of platforms. $Negative(x)$ is a dummy variable, which is 1 when x is negative and zeros otherwise. Control variables are $lnV_{i,t}$, $I_{i,t}$, $lnLS_{i,t}$ and $lnIA_{i,t}$ representing log platform scale (measured by trading volume), interest rates, log loan size per loan, and log investing amount per lender averaged within the t^{th} month of the i^{th} platform, respectively. $Time$ refers to the calendar month fixed effect, and $RelativeMonth$ represents the platform's age fixed effect in months since its inception.

Column (2) of Table 6 shows that the coefficient d_1 in equation (13) is significantly negative, indicating that lenders' p-CNEs are higher when platform scales trend up over the past year, both economically and statistically significantly. However, column (1) shows that the platform scale trend (albeit positive) has insignificant effects on borrowers' p-CNEs. These are consistent with the notion that the lenders' p-CNEs are smaller during the failing period shown in Table 5, whereas the borrowers' p-CNEs are rather symmetric in the initial and final stages of a platform's lifecycle.[27]

Overall, lenders' p-CNEs are asymmetric, being much lower during platform declines or when a platform is close to failing than during platform growth or during

[26] The reason to choose one year is that the loan issuing and the personal incomes normally have seasonality.
[27] Results in Table 6 remain robust when using the numbers of lenders and borrowers instead of trading volume as proxies for platform scale, although we leave out the detailed presentation for brevity.

platform inception. Borrowers' p-CNEs, in contrast, do not depend significantly on the status of platforms. In other words, lenders' p-CNEs are more sensitive to the platform's lifecycle stage and recent trend, relative to borrowers' p-CNEs, which is consistent with Hypothesis 1.

Since the lenders' p-CNEs are smaller on declining platforms relative to those on growing platforms, but borrowers' p-CNEs do not exhibit such features, the spread of borrowers' p-CNEs over the lenders' p-CNEs should be large for declining platforms. Therefore, there should be a positive relationship between the p-CNE gap and the indicator for platform declines. We therefore use the spread between borrowers' and lenders' p-CNEs as the dependent variable and rerun the regression model from equation (13). Column (3) of Table 6 shows that the p-CNE gap decreases on growing platforms: The p-CNE gap increases by 0.032 when the platform declines than when it grows. This is consistent with the notion that lenders' p-CNE is smaller in the declining platforms.[28]

5.3. Predicting Platform Failures

5.3.1. P-CNEs and Platform Failures

Since lenders' p-CNEs are different in periods of growth and stress, platforms with a high lender's p-CNE are likely in good shape. On the contrary, borrowers' p-CNEs cannot identify the status of the platforms because of their symmetric nature. These findings are consistent with the model presented in Section 4, which suggests that lenders' p-CNEs are crucial for predicting platform failure. To examine the relationship of p-CNEs and platform survival probability and test Hypothesis 2, we thus utilize the Fama-MacBeth regression to analyze the predictability of p-CNEs on the failure of different platforms and use the Newey-West method to adjust the standard errors of the estimation coefficients:

$$\begin{aligned} FA_{i,t+1} = {} & d_1 PCNE_{i,t}^{L} + d_2 PCNE_{i,t}^{B} + d_3 lnV_{i,t} + d_4 I_{i,t} + d_5 lnLS_{i,t} + d_6 lnIA_{i,t} \\ & + AgeDummy + u_{i,t+1}, \end{aligned} \tag{14}$$

[28] As a robustness check, we again use the number of borrowers and lenders instead of trading volume to be the proxy of the platform scale, and obtain consistent results.

where $FA_{i,t}$ is a dummy variable, which is set to 1 when the platform fails at the t^{th} month, and 0 otherwise. $PCNE_{i,t}^{L}$ and $PCNE_{i,t}^{B}$ are the lenders' and borrowers' p-CNEs, respectively, calculated with a one-year rolling window. t is indexed by calendar time in a monthly frequency from January 2015 to June 2018 (42 months).[29] The control variables are $lnV_{i,t}$, $I_{i,t}$, $lnLS_{i,t}$ and $lnIA_{i,t}$ representing log platform scale (measured by trading volume), interest rates, log loan size per loan, and log investing amount per lender averaged within the t^{th} month on the i^{th} platform, respectively. $AgeDummy$ is an age dummy that is grouped as $[1, 2, 3, 4, 5, > 5]$.[30] At each month t, we run a cross-sectional regression for all living platforms and then obtain a time series of coefficients for t. We use both OLS and logit models to perform regressions, respectively.

Table 7 demonstrates that the lenders' p-CNEs can strongly predict the platform's failure in both OLS and Logit regressions, respectively. A larger lender's p-CNE implies a lower rate of platform failure. For example, in column (3), one standard deviation increase in lenders' p-CNE leads to around 0.7% decrease in failure probability next month (8.4% on an annual basis). We also perform robustness checks with an alternative logit regression. The asymmetric impact of lenders' p-CNE on platform failure still manifests: larger lenders' p-CNEs result in a reduction of a platform's future failure rate significantly at the 1% level. These results are consistent with the model implications in Hypothesis 2: lenders' p-CNEs play a crucial role in forecasting the survival of marketplace lending platforms.

Note that the coefficient of borrowers' p-CNE is positive and partially significant in the OLS regression in column (1) but is negative and insignificant in the logit regression in column (4). The unstable sign and significance of borrowers' p-CNE is consistent with Hypothesis 2, which suggests that borrowers cannot reliably predict platform failure. When both lenders' and borrowers' p-CNEs are included

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[29] Figure B1 shows the yearly distribution of platform failures. We can observe that platform failures began in 2014, with a total of 19 platforms failing over the course of the year, averaging 1.58 failures per month. Therefore, the sample used in this analysis begins in 2015.

[30] At month t, if the platform's age is less than one year, it is grouped as 1. If the age is greater than or equal to one year but less than two years, it is grouped as 2, and so on. If the age is greater than or equal to five years, it is grouped as > 5.

simultaneously, the coefficient of the borrowers' p-CNE becomes significantly positive. The positive coefficient informs that a large borrowers' p-CNE leads to a larger failure rate, which is likely to be caused by the dramatic leaving of lenders during the failure period but a smaller amount of exit of borrowers.[31]

5.3.2. Early Prediction of Long-Run Survival

At this point, we have established a robust and stable relationship between lenders' p-CNEs and the likelihood of future platform failure through the Fama-MacBeth regression. Additionally, we have examined the relationship between borrowers' p-CNE, platform scale, interest rates, and other factors related to platform transaction size in relation to future platform failure. Moving forward, we aim to apply these findings to predict platform failure.

Platforms that survive 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' p-CNEs and the destiny (long-run failure or survival) of platforms. Specifically, we examine how p-CNEs calculated from the first year of a platform launch affect the failure rate in its future life by running a cross-sectional regression:

$$FA_{i,1} = d_0 + d_1 PCNE_{i,0}^{B} + d_2 PCNE_{i,0}^{L} + d_3 lnV_{i,0} + d_4 I_{i,0} + d_5 lnLS_{i,0} + d_6 lnIA_{i,0} + u_{i,1}, \tag{15}$$

where $PCNE_{i,0}^{L}$ and $PCNE_{i,0}^{B}$ are the lenders and borrowers' p-CNEs calculated for the first year of the i^{th} platform. Variables $lnV_{i,0}, I_{i,0}, lnLS_{i,0}$ and $lnIA_{i,0}$ are log trading volume, interest rates, log loan size per loan, 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 methods to estimate our regressions. Furthermore, we also analyze the life span of platforms using a Cox hazard model. In particular, we assume that the hazard rate $h_{i,1}$

[31] This is consistent with Table 5, where borrower's p-CNE is slightly larger in failing periods than take-off periods.

of the i^{th} platform depends on the p-CNEs of lenders and borrowers and other control variables in equation (15).

Table 8 reports the results. It is surprising that lenders' p-CNE in the first year has such a strong predicting power of future failures. If a platform has a large lenders' p-CNE at the inception, it is likely to face a relatively low failure rate during its whole life. From the OLS regression, one standard deviation increase in lenders' p-CNEs reduces 7% of the probability of platform failure.[32] This is consistent with previous findings 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' p-CNEs do not have such a predictive capability. Meanwhile, a low trading volume at the beginning also foretells a high rate of failure: one standard deviation increase in platform scales reduces 13.2% of the probability of platform failure. As a signal of low-quality loans, a high interest rate on a marketplace lending platform when it is initially launched also likely raises its future probability of failure. One standard deviation increase in interest rate increases 17.1% of the probability of platform failure.

In a sense, a platform has its destiny at birth, given its initial lenders' p-CNE, platform scale, and interest rates. As such, examining the characteristics and performance of a newborn platform after birth can provide valuable information for regulators and investors. If a marketplace lending platform at birth is unlucky to have a small lenders' p-CNE, its future failure is more likely.

6. Additional Analysis on P-CNE and Platform Failure

6.1. The Effect of the Non-Network Channel

The growth in the number of borrowers and lenders on a platform may occur through two channels: (a) network effect channel: the rapid positive feedback between incoming borrowers and lenders; (b) non-network effect channel:

[32] The standard deviation of first year lenders' p-CNE is 0.387.

unobserved variables driving up new borrowers and lenders simultaneously. For the non-network effect channel, a typical example is when a platform attracts significant attention upon its launch, thereby increasing awareness of the entire industry, and leading to a simultaneous rise in the number of lenders and borrowers on other platforms. Additionally, a platform's unobserved quality (e.g., advertisement, platform reputation, etc.) may also contribute to the simultaneous increase in lenders and borrowers.

In Section 5, we measure p-CNE using equations (11) and (12), which assume that the rapid growth during the inception phase is driven by positive feedback and ignores the possibility that unobserved factors might simultaneously drive the number of borrowers and lenders. To mitigate the impact of the non-network effect channel on our results, we further control for unobserved features that could simultaneously increase the number of new borrowers and lenders in (11) and (12). We introduce a variable, *Fast Start*, which refers to a platform that generates a very large number of trading volume during its first week, thereby increasing awareness of the entire industry and leading to a simultaneous increase in the number of lenders and borrowers on other platforms. Additionally, we include platform fixed effects in our empirical model to control for the impact of a platform's unobserved variables on the results and run the panel regressions,

$$\begin{aligned} lnN_{i,t+1}^{Inv} = b_0 + b_1 lnCN_{i,t}^{Borrower} + b_2 lnN_{i,t}^{Inv} + b_3 Fast\,Start_{i,t} + b_4 I_{i,t} + b_5\, ln\, LS_{i,t} \\ + b_6\, ln\, IA_{i,t} + Platform + Year + u_{i,t+1}, \end{aligned} \tag{16}$$

$$\begin{aligned} lnN_{i,t+1}^{Loan} = c_0 + c_1 lnCN_{i,t}^{Lender} + c_2 lnN_{i,t}^{Loan} + c_3 Fast\,Start_{i,t} + c_4 I_{i,t} + c_5\, ln\, LS_{i,t} \\ + c_6\, ln\, IA_{i,t} + Platform + Year + u_{i,t+1}, \end{aligned} \tag{17}$$

where $Fast\,Start_{i,t}$ takes value of one if during week t a newly launched platform (excluding platform i) records more than 1.67 million Yuan trading volume in its initial campaign week.[33] If the influence of Fast Start is controlled, and the coefficient b_1

[33] The threshold of 1.67 million Yuan represents the 75th percentile of first-week trading volumes across all platforms. If a platform's first-week trading volume exceeds this threshold, it can be considered to have generated significant attention at launch, which may increase overall attention to the industry and lead to simultaneous increases in both borrowers and lenders on other platforms.

and c_1 are still significant, then the non-network effect channel will not significantly impact the results already presented previously.

Table 9 shows the results of equations (16) and (17). We can observe that in both columns (1) and (2) the coefficient of $lnCN_{i,t}^{Borrower}$ and $lnCN_{i,t}^{Lender}$ are significant with large t statistic of 50.1 and 62.7, which means that the introducing of $Fast\ Start$ and fixed effect doesn't impact the results already presented. Additionally, the coefficients of $Fast\ Start$ are positive and significant, indicating that the non-network effect channel exists.[34] Overall, we conclude that the non-network effect channel does indeed influence the growth of lenders and borrowers, but the primary effect is still driven by p-CNE.

6.2. Determinants of First Year P-CNEs

In Table 8, we show that lenders' first-year p-CNEs have strong predictive power for platform failure. What, then, influences lenders' first-year p-CNEs? In this subsection, we analyze the critical socio-economic factors that influence p-CNEs during the take-off period (the first year after launch).

Table 10 shows that during the take-off period, platforms with VC backing have a significantly positive influence on both borrowers' and lenders' p-CNEs. In contrast, SOE endorsement has a significantly positive influence only on borrowers' p-CNEs, as an additional borrower tends to attract more lenders on SOE-backed platforms. This finding is consistent with Jiang et al. (2021), who demonstrate that SOE-backed platforms can attract more investors. However, lenders' p-CNEs do not appear to be affected by SOE endorsement. The population in the city where a certain platform is located influences both the borrowers' and lenders' p-CNEs, potentially due to investor home bias and better information networks in larger cities, but GDP does not. In theory, investors can come from all over the country, however, due to the home

[34] We also use the 75th percentile threshold of the number of borrowers and lenders to define $Fast\ Start_{i,t}$ and check whether the results are robust. The variable is assigned a value of one if, during week t, any newly launched platform, excluding platform i, generates over 10 borrowers or 123 lenders during its first campaign week. The results are shown in the Appendix Table B2.

bias documented in, for example, Coval and Moskowitz (1999), marketplace lending investors tend to prefer investing in local platforms.

6.3. Other Determinants of Platform Failure

Table 8 examines the predictive power of initial platform activity. Additionally, platform background and the political, economic, and regulatory environment may also drive platform failure. In this section, we further investigate how these factors affect platform failure using OLS regression.

First, we examine the impact of state-owned-enterprise (SOE) and venture capital (VC) backing on platform failure. An SOE-backed platform benefits from government endorsement, enhancing credibility and perceived lower risk, and VC-backed platforms, often funded early by venture capital, exhibit greater innovation and growth potential. From column (1) of Table 11, we can see that VC-backed platforms significantly reduce the likelihood of platform failure, with a t-statistic of 9.0, while SOE-backed cannot. Table 10 reveals that VC-backing is significantly associated with higher lender p-CNE in the first year, suggesting that the financial support from VC investors likely reduces platform failure by effectively scaling borrowers in the early stages of platform development. After introducing the SOE and VC backing variables into the prediction model, the R-squared value increases from 25.7% in Table 8 to 33.5% in column (1) of Table 11, underscoring the crucial role that financing background plays in determining the fate of these platforms.

We further examine the relationship between the platform's location demographics and platform failure. Column (2) of Table 11 suggest that platforms in cities with higher GDP per capita and larger populations have a lower probability of failure, though the results are not significant. Economically stronger and more populous areas offer a larger, potentially more stable user base, which may ensure consistent demand and greater resilience against economic fluctuations.

Lastly, we consider the effect of financial regulatory intensity on platform failure. Stricter financial regulation plays a crucial role in maintaining market order and reducing risks, thereby creating a more favorable environment for platform development. We measure this using a "Financial Constraint" variable derived from provincial financial regulatory expenditure in the platform's launch year, scaled from 0 to 1, with higher values indicating stricter regulation. As shown in column (2) of Table 11, platforms located in provinces with higher regulatory expenditure are less likely to fail, with a t-statistic of 2.6. This underscores the importance of a robust regulatory framework in promoting the longevity and stability of marketplace lending platforms. When we further introduce the above variables related to local economic development and regulatory policies into the model in column (1), the R-squared further increases to 34.9% in column (3).

7. Conclusion

Given the rapid emergence of FinTech platforms globally, we investigate how they differ from non-financial platforms. We argue that the default risks on marketplace lending and crowdfunding platforms lead to asymmetric stickiness of fundraisers and investors. Additionally, investment diversification mitigates idiosyncratic investment risks, but platform-level default risks and userbase dynamics interact, giving rise to the important role of platform-level cross-side network effects, a hitherto unexamined concept in the literature. We provide supporting evidence of the distinguishing features of FinTech platforms using a large panel dataset of marketplace lending platforms from China.

We then build a model of two-sided platforms that incorporates platform failures and the aforementioned features of financial platforms. The model predicts that lenders tend to single-home and could face higher fees than borrowers under certain conditions, which differs from the main competitive bottleneck situations on non-financial platforms. Furthermore, the model highlights the general asymmetry of p-CNEs on financial platforms, primarily due to the asymmetric stickiness of borrowers and lenders. In addition, the model demonstrates that lenders' p-CNEs serve as important predictors of platform failure.

We next verify the key model predictions empirically. We measure p-CNEs using the elasticity of participation from one side on the number of users from the other side. By calculating p-CNEs at different stages of the platform lifecycle, we find that while lenders’ p-CNEs are indeed asymmetrically larger on new and growing platforms compared to failing and declining platforms, borrowers’ p-CNEs exhibit no such asymmetry. Moreover, lenders’ p-CNEs can predict the future failure of marketplace lending platforms, even at very early stages.

Our study not only advances the fundamental understanding of multi-sided platforms and FinTech marketplaces but also provides valuable insights for platform owners, investors, and regulators. For example, our model demonstrates that the stickiness of borrowers makes them more valuable to the platform. Therefore, compared to non-financial platforms, attracting and retaining the multi-home side (borrowers on marketplace lending platforms) is more critical for FinTech platforms due to borrowers' reluctance to leave. Our findings also have broad implications for FinTech regulation. For example, regulators can closely monitor lenders’ p-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. Similarly, venture investors of the platforms and lenders can also monitor lenders’ p-CNEs to better manage their risks.

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Figures and Tables

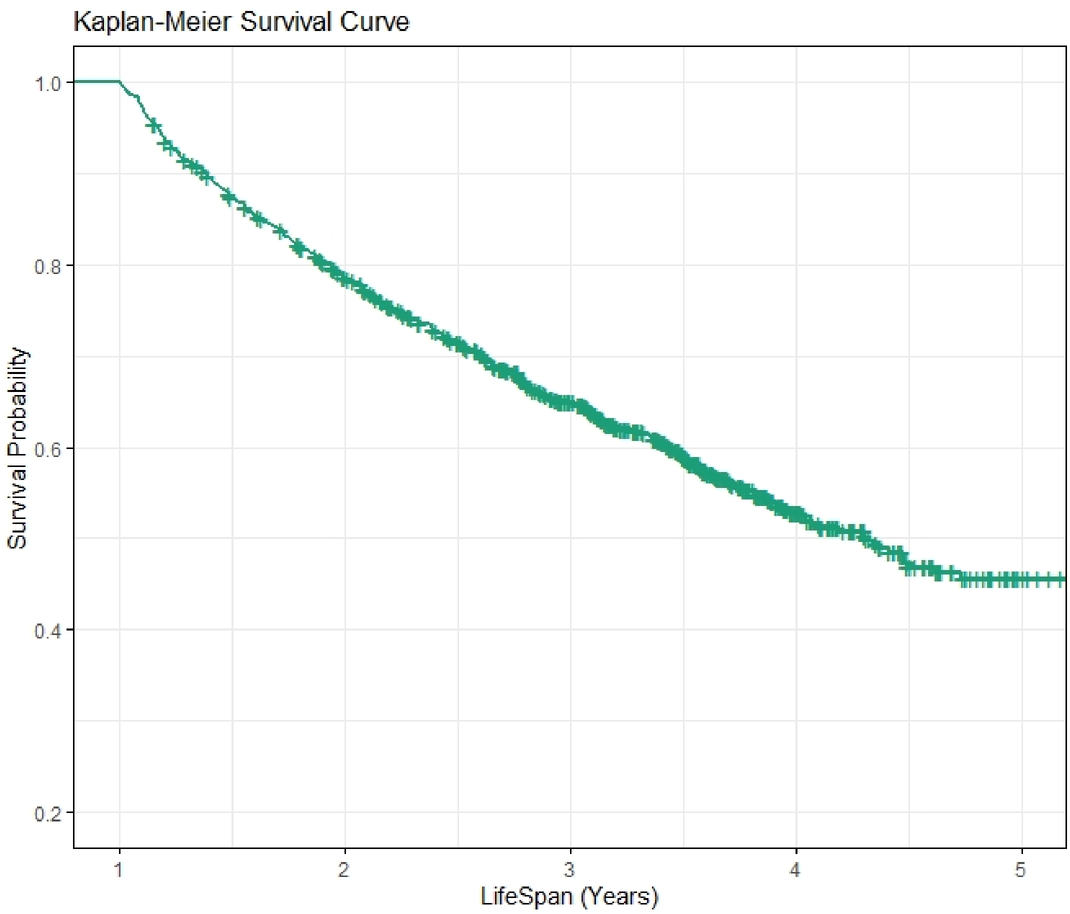

Figure 1. Kaplan-Meier Survival Rate vs. Platform Lifespan. This curve illustrates the relationship between platform lifespan (in years, on the x-axis) and survival probability (on the y-axis). It shows that platform survival decreases over time, particularly during the first few years of operation. After 4 years, the survival probability stabilizes, suggesting that platforms which survive this initial period have a relatively consistent chance of continued operation.

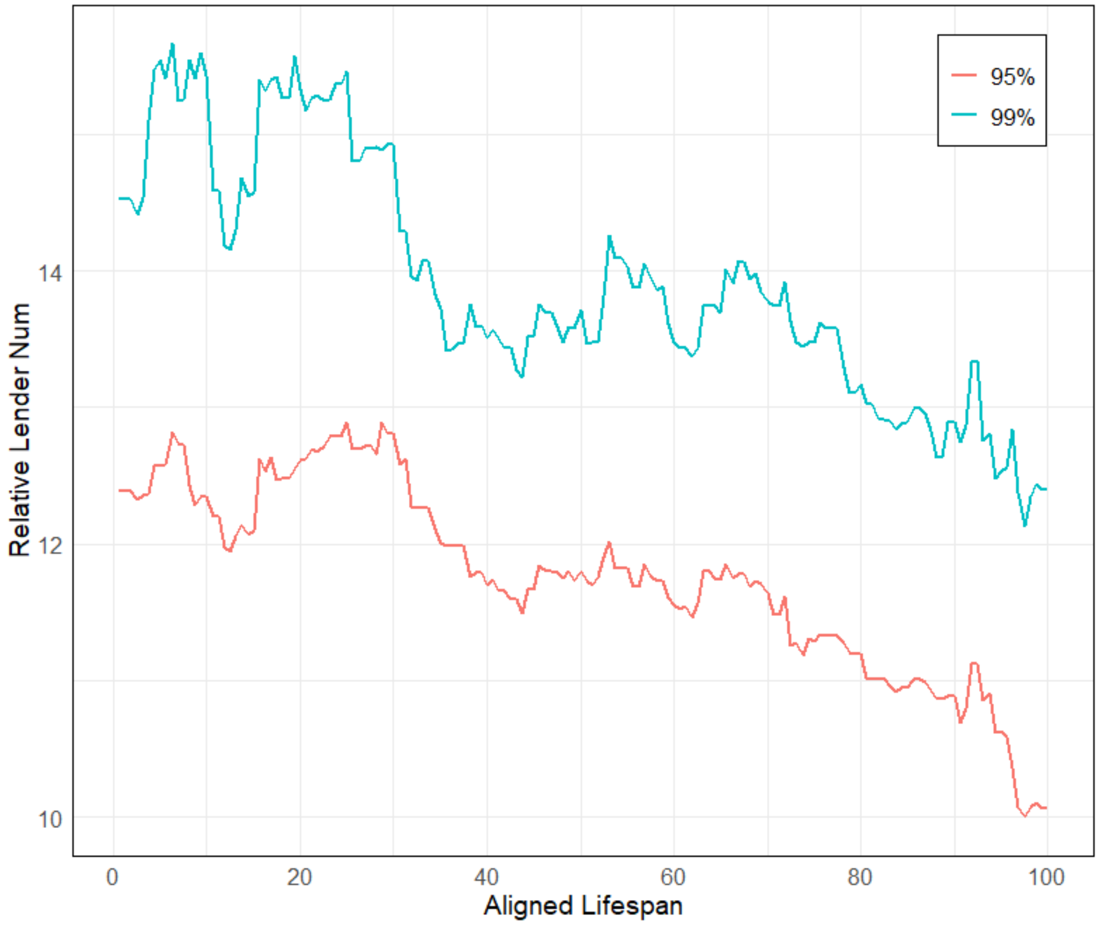

Figure 2. Ratio of Lenders to Borrowers for Failed Platforms Over Their Lifespan. This figure illustrates the ratio of lenders to borrowers (relative lender numbers) for failed platforms over their aligned lifespan (x-axis), where the lifespan is normalized to a range of [0,100]. The graph shows two lines representing the 95th percentile (red line) and the 99th percentile (blue line) of this ratio, tracking changes as platforms progress through their lifespan.

Table 1. Data Description

We analyze a total of 988 platforms, of which 418 (42.3%) failed, and 570 (57.7%) were still operating as of June 2018. In Panel A, we report the total number of platforms founded each year, those still surviving as of June 2018, and those that had failed by that time. We also calculate the average lifespan of both live and failed platforms. In Panel B, we present some basic characteristics of live and failed marketplace lending platforms. Metrics such as trading volume, average loan size, average investment size, amount per borrower, and amount per lender are reported in units of RMB 10,000.

Panel A: Marketplace Lending Platforms with Different Starting Years

Starting Year	≤2011	2012	2013	2014	2015	2016	≥2017	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 Lifespan (Live)	7.7	5.6	4.7	3.7	3.0	2.1	1.3	3.5
Average Lifespan (Failed)	4.9	3.3	2.4	2.1	2.0	1.5	-	2.2

Panel B: Various Features on Marketplace Lending Platforms

	Mean (all)	Std (all)	Mean (live)	Std (live)	Mean (failed)	Std (failed)
Trading Volume (log)	5.578	1.654	6.211	1.604	4.715	1.294
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
Average Loan Size (log)	2.857	1.075	3.051	1.093	2.592	0.993
Average 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

Table 2. Departures Before Platform Failures

Panel A of this table reports the change in the log numbers of borrowers and lenders up to 6 months before platform failures. Specifically, we first take the log of the average borrower's or lenders' number in a certain month before the platform's failure and then take the difference to the 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. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

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 3. Participation of Players before and after the Ezubao Collapse

We choose a 16-week (8 weeks before and 8 weeks after) window centered on the Ezubao closure date, December 8 2015, for 638 live platforms during this period. We perform the difference-in-differences regression, where the dependent variable is the number of borrowers or lenders at the week t of platform i; $dummy1$ is an indicator for the event that equals one in the weeks of and after December 8, 2015 and zero otherwise; $dummy2$ is a dummy variable that equals one for borrowers and zero for lenders. $lnV_{i,t}$, $I_{i,t}$, $lnLS_{i,t}$ and $lnIA_{i,t}$ are log trading volume, interest rates, log loan size per loan and log investing amount per lender within the week t on the platform i, respectively. Quantities in brackets are the t-statistics. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)
dummy1	-0.060***	-0.020**		
	(-3.012)	(-2.243)		
dummy2	-2.495***	-2.492***	-2.495***	-2.492***
	(-51.916)	(-51.730)	(-53.052)	(-53.472)
dummy1*dummy2	0.057***	0.047**	0.057***	0.047***
	(2.962)	(2.491)	(32.827)	(12.690)
$\boldsymbol{lnV_{i,t}}$		0.955***		0.954***
		(199.979)		(209.513)
$\boldsymbol{I_{i,t}}$		0.245		0.261*
		(1.592)		(1.865)
$\boldsymbol{lnLS_{i,t}}$		-0.439***		-0.439***
		(-61.051)		(-61.968)
$\boldsymbol{lnIA_{i,t}}$		-0.513***		-0.513***
		(-93.587)		(-91.431)
Platform FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
$\mathbf{R^2}$	73.7%	81.5%	73.7%	81.4%

Table 4. Summary Statistics of Platform-level Cross-Side Network Effects

This table presents the summary statistics of p-CNEs measured by equations (11) and (12), which capture the elasticity of investment (loan) numbers to the number of active lenders (borrowers). We report the average, standard deviation, maximum, minimum, and the proportion of positive and negative p-CNEs for both failed and live platforms. The correlation between borrowers' and lenders' p-CNEs is 0.53 for failed platforms and 0.44 for live platforms.

	Failed Platforms		**Live Platforms**	
	Borrowers' p-CNE, b_1	**Lenders' p-CNE, c_1**	**Borrowers' p-CNE, b_1**	**Lenders' p-CNE, c_1**
Average	0.152	0.147	0.146	0.191
Std Dev	0.508	0.409	0.467	0.461
Max	4.544	3.333	3.844	4.645
Min	-3.758	-1.738	-3.886	-2.479
Positive (%)	62.7%	63.8%	63.6%	67.4%
Negative (%)	37.4%	36.2%	36.4%	32.6%

Table 5. P-CNEs Throughout Platforms' Lifecycle

In this table, we group the p-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' p-CNEs in these three categories. Quantities in square brackets are standard deviations. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	One Year after Inception (P1)	**The Middle One Year (P2)**	**One Year before Failure (P3)**	**Diff (P3-P1)**
Borrowers' p-CNE	0.153	0.136	0.172	0.018
	[0.029]	[0.030]	[0.035]	[0.042]
Lenders' p-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 6. Asymmetry of Platform Level Cross-Side Network Effects

This table examines the asymmetry of platform-level Cross-Side Network Effects (p-CNEs). The dependent variable in columns (1) through (3) is the p-CNEs of the players (lenders or borrowers) and the spread between borrowers' and lenders' p-CNEs for the final week of the t^{th} month on the i^{th} platform, calculated using 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 log platform scale, interest rates, log loan size per loan and log investing amount per lender averaged within the t^{th} month on the i^{th} platform, respectively. $Time$ is the calendar month, and $RelativeMonth$ is the age of survival of the platform in months. Quantities in brackets are the t-statistics. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Borrowers' p-CNE	**Lenders' p-CNE**	**p-CNE Spread**
	(1)	(2)	(3)
$\boldsymbol{Negative(\Delta V_{i,t})}$	0.009	-0.023***	0.032***
	(0.781)	(-2.662)	(4.147)
$\boldsymbol{lnV_{i,t}}$	0.014**	0.024***	-0.011***
	(2.088)	(5.029)	(-3.273)
$\boldsymbol{I_{i,t}}$	-1.042***	-0.504***	-0.540***
	(-9.494)	(-8.049)	(-6.755)
$\boldsymbol{lnLS_{i,t}}$	-0.012***	-0.031***	0.019***
	(-3.181)	(-5.511)	(3.698)
$\boldsymbol{lnIA_{i,t}}$	-0.007	0.004***	-0.012**
	(-1.578)	(3.228)	(-2.331)
Time FE	YES	YES	YES
RelativeMonth FE	YES	YES	YES
R^2	0.032	0.037	0.025

Table 7. P-CNEs and Platform Failure

This table presents the predictability of borrower's and lenders' p-CNEs on platform failure via the Fama-MacBeth regression, where the dependent variable is a dummy variable that equals one when the i^{th} platform fails at month t+1, and 0 otherwise. $PCNE_{i,t}^{L}$ and $PCNE_{i,t}^{B}$ are the lenders' and borrowers' p-CNEs, respectively, calculated with a one-year rolling window. t is indexed by calendar time in a monthly frequency from January 2015 to June 2018 (42 months). $AgeDummy$ is an age dummy that is grouped as $[1,2,3,4,5,>5]$. $lnV_{i,t}$ denotes the platform scale level (trading volume) of platform i in month t. $I_{i,t}$, $lnLS_{i,t}$ and $lnIA_{i,t}$ are interest rates, log loan size per loan and log investing amount per lender averaged within the month t on the platform i, respectively. 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 42 lags. Quantities in brackets are the t-statistics. We use both OLS and logit model to perform regressions, respectively. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	OLS			Logit		
	(1)	(2)	(3)	(4)	(5)	(6)
$\boldsymbol{PCNE_{i,t}^{B}}$	0.005*		0.011***	-0.046		0.327**
	(1.798)		(2.959)	(-0.410)		(2.111)
$\boldsymbol{PCNE_{i,t}^{L}}$		-0.009***	-0.016***		-0.696***	-0.937***
		(-6.511)	(-5.995)		(-7.904)	(-9.356)
$\boldsymbol{lnV_{i,t}}$	-0.011***	-0.010***	-0.010***	-0.594***	-0.578***	-0.577***
	(-12.083)	(-12.076)	(-11.970)	(-11.700)	(-10.641)	(-9.685)
$\boldsymbol{I_{i,t}}$	-0.050*	-0.055**	-0.054**	1.864	1.985	1.918
	(-1.807)	(-2.142)	(-2.139)	(1.395)	(1.446)	(1.384)
$\boldsymbol{lnLS_{i,t}}$	-0.004***	-0.005***	-0.005***	-0.126***	-0.146***	-0.148***
	(-4.632)	(-5.016)	(-4.914)	(-2.777)	(-2.763)	(-2.683)
$\boldsymbol{lnIA_{i,t}}$	0.002	0.002	0.002	0.074	0.094**	0.083**
	(1.372)	(1.532)	(1.546)	(1.583)	(2.336)	(2.557)
Age Dummy	Yes	Yes	Yes	Yes	Yes	Yes
R^2	4.07%	4.19%	4.42%	5.08%	5.33%	5.57%

Table 8. Early-Stage P-CNEs and Marketplace Lending Platform Failure

This table shows how the first-year p-CNEs of a platform influence the future default. The dependent variable 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. $PCNE_{i,0}^{L}$ and $PCNE_{i,0}^{B}$ are the lenders' and borrowers' p-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 per loan and log investor's amount per lender averaged within the first year of the i^{th} platform, respectively. Both the OLS and logit regressions are used. We also analyze the lifespan of platforms using a Cox hazard model. The R^2 of the logit model is the McFadden R^2, and the R^2 of the Cox hazard model is the Cox-Snell R^2. Quantities in brackets are the t-statistics. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	OLS	**Logit**	**Cox**
	(1)	(2)	(3)
$\boldsymbol{PCNE_{i,0}^{B}}$	-0.015	-0.058	-0.113
	(-0.345)	(-0.256)	(-0.806)
$\boldsymbol{PCNE_{i,0}^{L}}$	-0.182***	-0.953***	-0.498***
	(-3.784)	(-3.489)	(-2.782)
$\boldsymbol{lnV_{i,0}}$	-0.080***	-0.479***	-0.316***
	(-5.261)	(-4.672)	(-5.462)
$\boldsymbol{I_{i,0}}$	4.385***	23.527***	10.170***
	(10.243)	(8.400)	(8.431)
$\boldsymbol{lnLS_{i,0}}$	-0.001	0.055	-0.060
	(-0.045)	(0.468)	(-0.781)
$\boldsymbol{lnIA_{i,0}}$	0.037	0.219*	0.135*
	(1.516)	(1.558)	(1.776)
$\mathbf{R^2}$	25.7%	21.3%	21.7%

Table 9. Non-Network Effect Channels in the Change of Lenders and Borrowers

This table introduces the variable $Fast\ Start$ and platform fixed effects to control for unobserved factors that may simultaneously drive increases in new borrowers and lenders, thereby testing the robustness of the p-CNEs measured in equations (11) and (12). The dependent variables of columns (1) and (2) are $lnN_{i,t+1}^{Inv}$ and $lnN_{i,t+1}^{Loan}$, respectively. $Fast\ Start_{i,t}$ takes a value of one if during week t a newly launched platform excluding platform i records more than 1.67 million Yuan in trading volume during its initial campaign week. Platform fixed effects are controlled for, and the year dummies refer to a series of calendar year dummy variables. Quantities in brackets are the t-statistics. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)
$\boldsymbol{lnCN_{i,t}^{Borrower}}$	0.205***	
	(50.147)	
$\boldsymbol{lnCN_{i,t}^{Lender}}$		0.250***
		(62.655)
$\boldsymbol{lnN_{i,t}^{Inv}}$	0.648***	
	(191.964)	
$\boldsymbol{lnN_{i,t}^{Loan}}$		0.612***
		(163.882)
$\boldsymbol{Fast\ Start_{i,t}}$	0.037***	0.030***
	(6.251)	(5.936)
$\boldsymbol{I_{i,t}}$	0.265**	0.298***
	(2.064)	(2.720)
$\boldsymbol{lnLS_{i,t}}$	0.061***	-0.250***
	(13.812)	(-57.603)
$\boldsymbol{lnIA_{i,t}}$	-0.088***	0.173***
	(-19.939)	(37.813)
Platform FE	Yes	Yes
CalendarYear FE	Yes	Yes
R^2	93.1%	94.1%

Table 10. Critical Factors Influencing the First Year P-CNEs

In this table, we analyze the critical factors influencing the p-CNEs for the take-off period (first year after launch). We run a cross-sectional regression, the dependent variable is the borrowers' ($PCNE_i^B$) or lenders' ($PCNE_i^L$) p-CNEs. SOE_i is a dummy variable that equals 1 if platform i is invested by state-owned enterprises, and VC_i is a dummy variable that equals 1 when platform i is invested by VCs. $\log(GDP_i)$ and $\log(Population_i)$ are the log value of GDP and population of a city where the platform is located, respectively. $LauchYear$ is a series of dummy variables that equals 1 if the platform i was launched in the year (≤2011, 2012, 2013, 2014, 2015, 2016, ≥2017). Quantities in brackets are the t-statistics. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Borrowers' p-CNE	**Lenders' p-CNE**
	(1)	(2)
$\boldsymbol{SOE}$	0.192**	0.003
	(2.441)	(0.073)
$\boldsymbol{VC}$	0.096**	0.159***
	(2.210)	(4.172)
$\boldsymbol{log(GDP)}$	0.046	0.005
	(0.862)	(0.115)
$\boldsymbol{log(Population)}$	0.083***	0.072***
	(2.758)	(2.944)
LaunchYear FE	Yes	Yes
$\mathbf{R^2}$	4.3%	6.3%

Table 11. Early-Stage P-CNEs and Marketplace Lending Platform Failure

This table shows how the variables related to the platform's background and the political and economic characteristics of platform's location influence platform failure using OLS regression. SOE is a dummy variable that equals 1 if platform i is supported or partially owned by Chinese state-owned enterprises, VC is a dummy variable that equals 1 if when platform i is invested by VCs. $log(GDP_i)$ and $log(Population_i)$ are the log value of GDP and population of a city where the platform is located at launch year, and $Financial\ Constraint$ denote the value of financial regulatory expenditure in the launch year in the province where the platform was established. Quantities in brackets are the t-statistics. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)
$PCNE_{i,0}^{B}$	-0.028	-0.019	-0.033
	(-0.727)	(-0.445)	(-0.856)
$PCNE_{i,0}^{L}$	-0.112**	-0.186***	-0.114**
	(-2.448)	(-3.845)	(-2.479)
$lnV_{i,0}$	-0.057***	-0.074***	-0.055***
	(-3.770)	(-4.807)	(-3.588)
$I_{i,0}$	3.953***	4.183***	3.771***
	(9.238)	(9.073)	(8.144)
$lnLS_{i,0}$	0.010	-0.007	0.007
	(0.537)	(-0.333)	(0.361)
$lnIA_{i,0}$	-0.001	0.042*	0.004
	(-0.059)	(1.755)	(0.172)
SOE	0.048		0.049
	(0.667)		(0.663)
VC	-0.352***		-0.356***
	(-9.023)		(-9.053)
$log(GDP)$		-0.089*	-0.040
		(-1.743)	(-0.860)
$log(Population)$		-0.013	-0.018
		(-0.385)	(-0.602)
$Financial\ Constraint$		-7.866***	-9.141***
		(-2.597)	(-3.052)
R^2	33.5%	27.1%	34.9%

Appendix A. Institutional details on Chinese Marketplace Lending

A.1. China's Marketplace Lending: History, Growth, and Scale

Marketplace lending was first introduced in China in 2007. While having a later start than the US and UK, the Chinese marketplace lending 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 marketplace lending 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 marketplace lending and the transaction volume amounted to US $178.89 billion, as compared to US $8.21 billion in the United States.[35]

One potential facilitator of the rapid growth in China's marketplace 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 (Zhou, Arner, and Buckley, 2015).

Tightening regulation and cracking down of platforms that fail to meet the standard were executed after June 2018. The number of platforms dropped by more than 50 percent to 1,021 at the end of 2018 due to failing to comply with the regulations.[36] Brusa, Luo, and Fang (2019) summarized three distinctive features of China's situation that catalyzed the fast growth of China's marketplace 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.2. Mechanics of China's Marketplace Lending Platform

Looking at the top 5 marketplace lending platforms of China (marketplace lending platform surveyed: Lujinfu, Jiufupuhui, Yirendai, Renrendai, Aiqianjin), we see that

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[35] Statistia Research Department, 2019, Alternative Lending Transaction Value in Countries Worldwide 2018, https://www.statista.com/statistics/497241/digital-market-outlook-global-comparison-alternative-lending-transaction-value/.

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

most of them offer loans in three types of format: (1) Individual loans for direct investments; (2) A portfolio of loans or platform's product; (3) The secondary market for loans originated in the platform. Song et al. (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 have attracted enough lenders to reach the targeted funding amount, the loan is funded and at this stage, the marketplace lending platform's focus becomes ensuring the borrowers pay back the loan on time. Lenders can choose to wait for borrowers' regular payments, or sell their debts to other investors. If borrowers fail to pay off all the money on the due date, sometimes, a third party (the insurance company) might be involved to help recover the lenders' loss.

A.3. Fee Structure of Marketplace Lending Platforms

As a facilitator in matching borrowers and lenders, China's marketplace lending platforms obtain their revenues through origination fees collected from the matchmaking process. Marketplace lending platforms in China charge a proportional fees to borrowers based on their financing amount, and to lenders based on either their investment amount or investment returns. Additionally, many platforms, such as Renrendai, do not charge fees to lenders.

A.4. 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 marketplace lending markets, which takes several steps until the loan is finally issued.

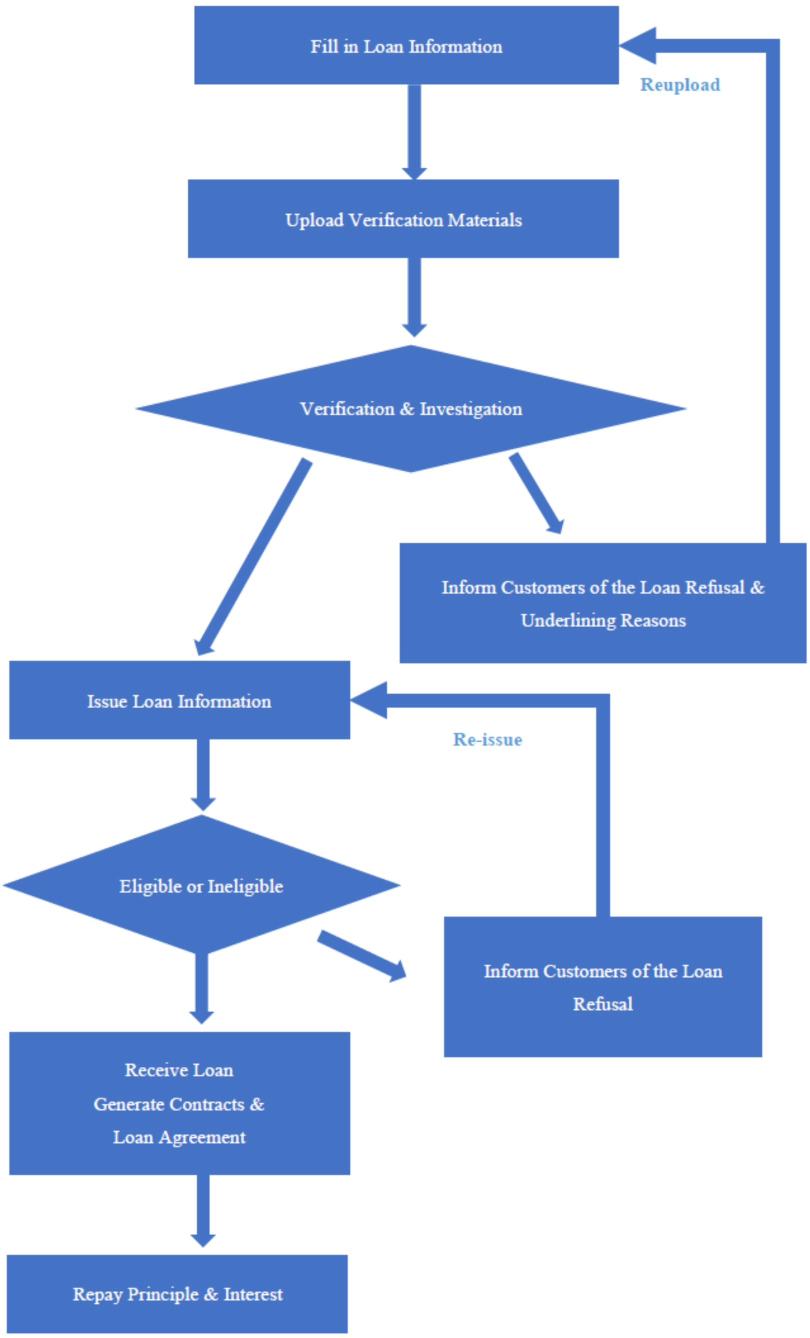

Figure A1. Flow Chart of the Loan Application Process.

A.5. Platform Failures

There are many reasons for which a marketplace lending platform may fail. The main reason is that many platforms neglect the importance of risk management or promise unreasonably high rates of return. They attract low-quality borrowers and have a high rate of non-performing loans (and hence high interest rates). As a result, the platform becomes unsustainable and ultimately shuts down. Furthermore, the economic slowdown contributed to the massive failure of Chinese marketplace lending 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 following case study provides more details on the failure mechanisms affecting the majority of platforms.

Funded in Yibin and grown in Chengdu, Sida Investment (www.sidatz.com, this website is no longer accessible.) has a transaction volume of over 1.7 billion yuan and is the fourth largest marketplace lending 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 marketplace lending 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 Non-Performing Loan (NPL) since its inception. After nine months of operation, the total transaction amount reached 30 million yuan, and the NPL ratio was as high as 60%. Due to the high ratio of NPL, other Sida shareholders started to withdraw their shares and Sida eventually became the sole proprietorship platform of Mr. Jian He.

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

However, facing a deteriorating macroeconomic environment and the decline in market demand, the price of rosewood furniture continued to fall, and finally even fell to a five-year low. Many borrowers cannot repay their loans. As a result, the NPL ratio of Sida Investment had kept growing until the first half of 2016.

Sida Investment is a typical “grassroots” startup. In the beginning, almost no staff understood how marketplace lending financial platform works. However, this platform had been grown fast and once ranked top 100 in the whole marketplace lending industry. Mr. Jian He, the sole owner of the platform, established his absolute authority over the management team. With little awareness of risk management, Sida’s business is gradually shrinking while risks accumulating over time. It is not surprising that the main reason for the withdrawal difficulties of Sida is the serious problem of NPLs. It is estimated that the platform’s NPLs has exceeded 50 million yuan.

Appendix A References

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Appendix B. Appendix Figures and Tables

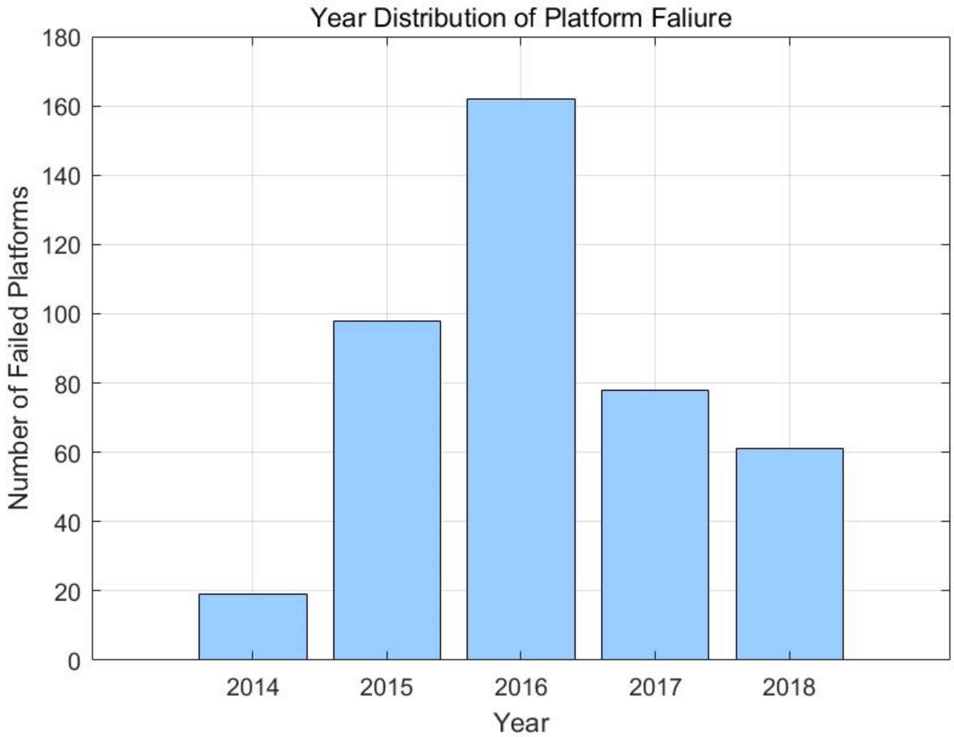

Figure B1. Year Distribution of Platform Failure. The figure plots the number of platform failures each year. Platform failures began in 2014, with 19 platforms closing that year. The number of failures rapidly increased to 98 in 2015, further rising to 162 in 2016. In 2017, 78 platforms failed, and by June 30, 2018, a total of 61 platforms had closed.

Table B1. Lenders' Investment Diversification

This table reports the lenders' investment diversification by running the following two panel regressions:

$$lnDI_{i,t+1}^{K} = d_0 + d_2 lnN_{i,t}^{Borrower} + d_3 I_{i,t} + d_4 lnLS_{i,t} + d_5 lnIA_{i,t} + d_6 lnDI_{i,t} + Platform + Time + u_{i,t+1}$$

where $DI_{i,t}^{K}$ $(K = N, A)$ are the average number of investments per lender and average amount per investment, respectively, in the platform i at the month t. $I_{i,t}$, $LS_{i,t}$ and $IA_{i,t}$ are interest rates, average loan size, and investing amount per lender averaged for platform i at month t, respectively. Quantities in brackets are the t-statistics. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Average number of investments per lender		**Average Amount per Investment**	
	(1)	(2)	(3)	(4)
$\boldsymbol{lnN_{i,t}^{Borrower}}$	0.012***	0.007***	-0.029***	-0.027***
	(4.395)	(3.337)	(-4.653)	(-3.540)
$\boldsymbol{I_{i,t}}$		-0.040		-0.154
		(-0.472)		(-0.525)
$\boldsymbol{lnLS_{i,t}}$		-0.021**		-0.013
		(-2.990)		(-0.794)
$\boldsymbol{lnIA_{i,t}}$		0.011		-0.043
		(1.004)		(-1.349)
$\boldsymbol{lnDI_{i,t}^{N}}$	0.766***	0.756***		
	(20.352)	(19.775)		
$\boldsymbol{lnDI_{i,t}^{A}}$			0.646***	0.696***
			(22.742)	(13.171)
Platform FE	YES	YES	YES	YES
CalendarYear FE	YES	YES	YES	YES
$\mathbf{R^2}$	84.4%	84.5%	84.8%	85.0%

Table B2. Robustness Check Concerning Non-Network-Effect Channels in the Growth of Lenders and Borrowers

We introduce a variable, Fast Start and platform fixed effects to control for the impact of unobserved variables driving up new borrowers and lenders simultaneously. $Fast\ Start_{i,t}$ takes value of one if during week t a newly launched platform excluding platform i records more than 10 borrowers (columns (1) and (3)) or 123 lenders (columns (2) and (4)) in its initial campaign week. Quantities in brackets are the t-statistics. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)
$lnCN_{i,t}^{Borrower}$	0.205***	0.205***		
	(50.141)	(50.097)		
$lnCN_{i,t}^{Lender}$			0.250***	0.250***
			(62.665)	(62.631)
$lnN_{i,t}^{Inv}$	0.648***	0.648***		
	(191.912)	(191.984)		
$lnN_{i,t}^{Loan}$			0.612***	0.612***
			(163.841)	(163.875)
$Fast\ Start_{i,t}$	0.019***	0.017***	0.015***	0.014***
	(3.529)	(2.880)	(3.287)	(2.874)
$I_{i,t}$	0.269**	0.269**	0.302***	0.301***
	(2.093)	(2.095)	(2.749)	(2.746)
$lnLS_{i,t}$	0.061***	0.061***	-0.250***	-0.249***
	(13.856)	(13.856)	(-57.558)	(-57.524)
$lnIA_{i,t}$	-0.088***	-0.088***	0.172***	0.172***
	(-19.977)	(-19.982)	(37.779)	(37.742)
Platform FE	Yes	Yes	Yes	Yes
CalendarYear FE	Yes	Yes	Yes	Yes
R^2	93.1%	93.1%	94.1%	94.1%

Appendix C

Proof of Lemma 1.

To demonstrate that lenders single-home, we show that lenders do not gain additional utility from joining more than one platform, i.e., they single-home. Consider the benchmark market structure where lenders single-home and borrowers multi-home. From the participation analysis of borrowers, the install base of borrowers across platforms satisfies either $\widehat{N}_b^A \subseteq \widehat{N}_b^B$ or $\widehat{N}_b^B \subseteq \widehat{N}_b^A$.

Assume that there exists x_0 such that $U_{l,x_0}^A = U_{l,x_0}^B$. If no such x_0 exists, i.e., $\nexists x_0\ s.t. U_{l,x_0}^A = U_{l,x_0}^B$, one of the platforms would attract no lenders and could thus be excluded from consideration. Without loss of generality, we focus on whether a lender initially on platform B would multi-home. A lender on platform B, located at $x > x_0$, will multi-home if and only if:

$$U_{l,x}^{A,B} - U_{l,x_0}^B = \alpha(s)\left(\widehat{N}_b^{A,B} - \widehat{N}_b^B\right) + k[\lambda^A(1+R^A) - \lambda^B(1+R^B)] - P_l^A - tx \geq 0, \qquad \text{(A.1)}$$

where $\widehat{N}_b^{A,B} = \widehat{N}_b^A \cup \widehat{N}_b^B$.

Next, we analyze different relationships between $\lambda^A(1+R^A)$ and $\lambda^B(1+R^B)$.

Case 1. If $\lambda^A(1+R^A) = \lambda^B(1+R^B)$, then we have:

$$U_{l,x}^{A,B} - U_{l,x_0}^B = \alpha(s)\left(\widehat{N}_b^{A,B} - \widehat{N}_b^B\right) - P_l^A - tx \leq \alpha(s)\left(\widehat{N}_b^{A,B} - \widehat{N}_b^B\right) - P_l^A - tx_0.$$

If $\widehat{N}_b^A \subseteq \widehat{N}_b^B$, i.e. $\widehat{N}_b^{A,B} = \widehat{N}_b^B$, then $U_{l,x}^{A,B} - U_{l,x_0}^B \leq -P_l^B + tx_0 - t$.

If $\widehat{N}_b^B \subseteq \widehat{N}_b^A$, i.e. $\widehat{N}_b^{A,B} = \widehat{N}_b^A$, according to $U_{l,x_0}^A = U_{l,x_0}^B$, we can derive that:

$$\begin{aligned}\alpha(s)\left(\widehat{N}_b^{A,B} - \widehat{N}_b^B\right) &= \alpha(s)\left(\widehat{N}_b^A - \widehat{N}_b^B\right) \\ &= -(\lambda^A(1+R^A) - \lambda^B(1+R^B)) + P_l^A - P_l^B + 2tx_0 - t.\end{aligned}$$

Thus $U_{l,x}^{A,B} - U_{l,x_0}^B \leq -P_l^B + tx_0 - t$. Since $x_0 \leq 1$, $U_{l,x}^{A,B} - U_{l,x_0}^B < 0$. Therefore, in this case, a lender on platform B has no incentive to multi-home, as no additional utility is gained.

Case 2. If $\lambda^A(1+R^A) \neq \lambda^B(1+R^B)$. We first consider $\lambda^A(1+R^A) > \lambda^B(1+R^B)$. A lender on platform B, located at $x > x_0$, will multi-home if and only if equation (A.1) holds. By the lender's optimal capital allocation, if the lender multi-home, it will set $k \to 1$. Therefore:

$$U_{l,x}^{A,B} - U_{l,x_0}^{B} \leq \alpha(s)\left(\widehat{N}_b^{A,B} - \widehat{N}_b^{B}\right)+[\lambda^A(1+R^A) - \lambda^B(1+R^B)] - P_l^A - tx_0.$$

If $\widehat{N}_b^A \subseteq \widehat{N}_b^B$, i.e. $\widehat{N}_b^{A,B} = \widehat{N}_b^B$, then

$$U_{l,x}^{A,B} - U_{l,x_0}^{B} \leq [\lambda^A(1+R^A) - \lambda^B(1+R^B)] - P_l^A - tx_0.$$

By a similar argument derived from $U_{l,x_0}^{A} = U_{l,x_0}^{B}$, we have $U_{l,x}^{A,B} - U_{l,x_0}^{B} \leq -P_l^B + tx_0 - t < 0$.

If $\widehat{N}_b^B \subseteq \widehat{N}_b^A$, i.e. $\widehat{N}_b^{A,B} = \widehat{N}_b^A$, we similarly have:

$$U_{l,x}^{A,B} - U_{l,x_0}^{B} \leq \alpha(s)\left(\widehat{N}_b^{A} - \widehat{N}_b^{B}\right)+[\lambda^A(1+R^A) - \lambda^B(1+R^B)] - P_l^A - tx_0$$

$$= -P_l^B + tx_0 - t < 0.$$

If $\lambda^A(1+R^A) < \lambda^B(1+R^B)$, the lender on platform B has even weaker motivation to multi-home. Strictly speaking, by a similar argument as in the case $\lambda^A(1+R^A) > \lambda^B(1+R^B)$, we conclude that lenders on platform B will not join A simultaneously, i.e. single-home. Thus, in all cases, lenders have no incentive to multi-home.

Q.E.D.

Proof of Proposition 1

We first consider the lenders' heterogeneous outside option value. Lenders will choose to participate in if $U_l - v_l \geq 0$, which means $v_l \leq U_l$, and $N_l = \frac{U_l}{Z}$. Similarly, borrowers will participate if $U_b - v_b \geq 0$, which means $v_b \leq U_b$, and $N_b = \frac{U_b}{Z}$. According to Armstrong (2006), we consider the platform to be determining the agents' utilities $\{U_l, U_b\}$ rather than prices $\{P_l, P_b\}$. Then the profit maximum problem in equation (4) is transferred to,

$$\max_{U_l,U_b} \pi\,(U_l, U_b)$$
$$= \frac{U_l}{Z}\left[\alpha(s)\widehat{N}_b + \lambda(1+R) - 1 - U_l - f_l\right] + \frac{U_b}{Z}\left[\beta(s)\widehat{N}_l - \lambda(1+R)Q + Q - U_b - f_b\right]. \tag{A.2}$$

We can obtain the F.O.C. w.r.t U_l and U_b,

$$\frac{\partial\pi}{\partial U_l} = \frac{\alpha(s)\widehat{N}_b - f_l - (1-\lambda-\lambda R) - 2U_l}{Z},$$
$$\frac{\partial\pi}{\partial U_b} = \frac{\beta(s)\widehat{N}_l - f_b + Q(1-\lambda-\lambda R) - 2U_b}{Z}. \tag{A.3}$$

Combine equation (A.3) and market clearing condition $N_l = N_b Q$, we can get,

$$U_b^* = \frac{\beta(s)\widehat{N}_l - f_b + (\alpha(s)\widehat{N}_b - f_l)Q}{2 + 2Q^2},$$
$$U_l^* = \frac{\beta(s)\widehat{N}_l - f_b + (\alpha(s)\widehat{N}_b - f_l)Q}{2 + 2Q^2} \cdot Q, \tag{A.4}$$
$$R^* = \frac{1 - (\alpha(s)\widehat{N}_b - f_l) + Q(\beta(s)\widehat{N}_l - f_b + Q) - \lambda(1 + Q^2)}{\lambda(1 + Q^2)}.$$

Using equation (A.4), we can derive that,

$$N_b^* = \frac{U_b^*}{Z} = \frac{\beta(s)\widehat{N}_l - f_b + (\alpha(s)\widehat{N}_b - f_l)Q}{(2 + 2Q^2)Z},$$
$$N_l^* = \frac{U_l^*}{Z} = \frac{\beta(s)\widehat{N}_l - f_b + (\alpha(s)\widehat{N}_b - f_l)Q}{(2 + 2Q^2)Z} \cdot Q. \tag{A.5}$$

The profit-maximizing prices satisfy,

$$P_b^* = f_b + \frac{\beta(s)\widehat{N}_l - f_b + (\alpha(s)\widehat{N}_b - f_l)Q}{2 + 2Q^2} > f_b,$$
$$P_l^* = f_l + \frac{\beta(s)\widehat{N}_l - f_b + (\alpha(s)\widehat{N}_b - f_l)Q}{2 + 2Q^2} \cdot Q > f_l. \tag{A.6}$$

The lenders' p-CNE is $\frac{\partial N_b}{\partial \widehat{N}_l} \cdot \frac{\widehat{N}_l}{N_b}$, the borrowers' p-CNE is $\frac{\partial N_l}{\partial \widehat{N}_b} \cdot \frac{\widehat{N}_b}{N_l}$, we can derive that,

$$CNE_l = \frac{\partial N_b^*}{\partial \widehat{N}_l} \cdot \frac{\widehat{N}_l}{N_b^*} = \frac{\beta(s)}{(2 + 2Q^2)Z} \cdot \frac{\widehat{N}_l}{N_b^*} = \frac{\beta(s)\widehat{N}_l}{\beta(s)\widehat{N}_l - f_b + (\alpha(s)\widehat{N}_b - f_l)Q},$$
$$CNE_b = \frac{\partial N_l^*}{\partial \widehat{N}_b} \cdot \frac{\widehat{N}_b}{N_l^*} = \frac{\alpha(s)}{(2 + 2Q^2)Z} \cdot Q^2 \cdot \frac{\widehat{N}_b}{N_l^*} = \frac{\alpha(s)\widehat{N}_b Q}{\beta(s)\widehat{N}_l - f_b + (\alpha(s)\widehat{N}_b - f_l)Q}. \tag{A.7}$$

Since $\alpha(H) = \alpha(L) = \alpha$, both CNE_l and CNE_b will change with $\beta(s)$. As $\beta(s)$ is increasing with respect to s, by $\frac{\partial CNE}{\partial s} = \frac{\partial CNE}{\partial \beta(s)} \cdot \frac{\partial \beta(s)}{\partial s}$, we only need to calculate the derivative with respect to $\beta(s)$ to determine the monotonicity of $CNE(s)$.

$$\frac{\partial CNE_l}{\partial \beta(s)} = \frac{\widehat{N}_l(-f_b + (\alpha(s)\widehat{N}_b - f_l)Q)}{(\beta(s)\widehat{N}_l - f_b + (\alpha(s)\widehat{N}_b - f_l)Q)^2},$$
$$\frac{\partial CNE_b}{\partial \beta(s)} = -\frac{\alpha\widehat{N}_b\widehat{N}_l Q}{\left(\beta(s)\widehat{N}_l - f_b + (\alpha(s)\widehat{N}_b - f_l)Q\right)^2}. \tag{A.8}$$

Cause $f_b = f_l = 0$, we have $\frac{\partial CNE_l}{\partial \beta(s)} > 0$ and $\frac{\partial CNE_b}{\partial \beta(s)} < 0$. Due to $\beta(H) > \beta(L)$, we have $CNE_l|_{s=H} > CNE_l|_{s=L}$, and $CNE_b|_{s=H} < CNE_b|_{s=L}$.

Q.E.D.

Proof of Proposition 2

Social planner's problem,

$$SW(U_l, U_b) = \pi(U_l, U_b) + AU_l + AU_b, \tag{A.9}$$

where $AU_k\ (k = l, b)$ is the aggregate utilities of lenders and borrowers, respectively. $AU_k = \frac{1}{2}Z + \frac{1}{2Z}U_k^2$. Combine F.O.C. w.r.t U_l and U_b derived by equation (A.9) and the market clearing condition, we can get

$$\begin{aligned} U_b^s &= \frac{\beta(s)\widehat{N}_l - f_b + (\alpha(s)\widehat{N}_b - f_l)Q}{1 + Q^2}, \\ U_l^s &= \frac{\beta(s)\widehat{N}_l - f_b + (\alpha(s)\widehat{N}_b - f_l)Q}{1 + Q^2} \cdot Q, \\ R^s &= \frac{1 - (\alpha(s)\widehat{N}_b - f_l) + Q(\beta(s)\widehat{N}_l - f_b + Q) - \lambda(1 + Q^2)}{\lambda(1 + Q^2)}. \end{aligned} \tag{A.10}$$

Then we can derive that,

$$\begin{aligned} N_b^s &= \frac{U_b^*}{Z} = \frac{\beta(s)\widehat{N}_l - f_b + (\alpha(s)\widehat{N}_b - f_l)Q}{(1 + Q^2)Z}, \\ N_l^s &= \frac{U_l^*}{Z} = \frac{\beta(s)\widehat{N}_l - f_b + (\alpha(s)\widehat{N}_b - f_l)Q}{(1 + Q^2)Z} \cdot Q. \end{aligned} \tag{A.11}$$

Here, the lenders' and borrowers' CNE are,

$$\begin{aligned} CNE_l &= \frac{\partial N_b^s}{\partial \widehat{N}_l} \cdot \frac{\widehat{N}_l}{N_b^s} = \frac{\beta(s)}{(1 + Q^2)Z} \cdot \frac{\widehat{N}_l}{N_b^s} = \frac{\beta(s)\widehat{N}_l}{\beta(s)\widehat{N}_l - f_b + (\alpha(s)\widehat{N}_b - f_l)Q}, \\ CNE_b &= \frac{\partial N_l^s}{\partial \widehat{N}_b} \cdot \frac{\widehat{N}_b}{N_l^s} = \frac{\alpha(s)}{(1 + Q^2)Z} \cdot Q^2 \cdot \frac{\widehat{N}_b}{N_l^s} = \frac{\alpha(s)\widehat{N}_b Q}{\beta(s)\widehat{N}_l - f_b + (\alpha(s)\widehat{N}_b - f_l)Q}. \end{aligned} \tag{A.12}$$

The socially optimal prices,

$$\begin{aligned} P_b^s &= f_b, \\ P_l^s &= f_l. \end{aligned} \tag{A.13}$$

Comparing the socially optimal equilibrium with the equilibrium in Proposition 1, we see that $P_b^s < P_b^*$ and $P_l^s < P_l^*$. The higher prices distort the equilibrium, reducing the utility of entering the platform for both lenders and borrowers, resulting in under-participation.

Q.E.D.

Proof of Proposition 3

Equations (8) and (9) show the number of borrowers and lenders joining platform $i = A, B$. The platform i's expected profit is given by

$$\max_{P_l, P_b} \pi^i(P_l^i, P_b^i) = N_l^i(P_l^i - f_l) + N_b^i(P_b^i - f_b). \tag{A.14}$$

The F.O.C w.r.t P_l^i and P_b^i are

$$\frac{\partial \pi^i}{\partial P_l^i} = \frac{f_l + \alpha(s)(\widehat{N}_b^i - \widehat{N}_b^{-i}) + (\lambda^i - \lambda^{-i})(1 + R^i) - 2P_l^i + P_l^{-i} + t}{2t},$$

$$\frac{\partial \pi^i}{\partial P_b^i} = \frac{f_b + \beta(s)\widehat{N}_l^i + Q(1 - \lambda^i - \lambda^i R^i) - 2P_b^i}{Z}. \tag{A.15}$$

Combine F.O.C and market clearing conditions, we can obtain

$$P_b^A = f_b + \frac{Z(Q(\beta(s)(\widehat{N}_l^A - \widehat{N}_l^B) + \alpha(s)(\widehat{N}_b^A - \widehat{N}_b^B)Q + 3Qt) + 2Z)}{6Q^3t + 4QZ},$$

$$P_b^B = f_b + \frac{Z(Q(\beta(s)\left(\widehat{N}_l^B - \widehat{N}_l^A\right) + \alpha(s)\left(\widehat{N}_b^B - \widehat{N}_b^A\right)Q + 3Qt) + 2Z)}{6Q^3t + 4QZ},$$

$$P_l^A = f_l + t + \frac{Q(\beta(s)\left(\widehat{N}_l^A - \widehat{N}_l^B\right) + \alpha(s)(\widehat{N}_b^A - \widehat{N}_b^B)Q)t}{3Q^2t + 2Z},$$

$$P_l^B = f_l + t + \frac{Q(\beta(s)\left(\widehat{N}_l^B - \widehat{N}_l^A\right) + \alpha(s)(\widehat{N}_b^B - \widehat{N}_b^A)Q)t}{3Q^2t + 2Z},$$

$$\begin{aligned} R^A &= \frac{3Q^3(-f_b + \beta(s)\widehat{N}_l^A + Q - \lambda^A Q)t}{\lambda^A Q^2(3Q^2t + 2Z)} \\ &+ \frac{Q(-2f_b + \beta(s)(\widehat{N}_l^A + \widehat{N}_l^B) + Q(2 - 2\lambda^A + \alpha(s)\left(-\widehat{N}_b^A + \widehat{N}_b^B\right) - 3t))Z - 2Z^2}{\lambda^A Q^2(3Q^2t + 2Z)}, \end{aligned} \tag{A.16}$$

$$\begin{aligned} R^B &= \frac{3Q^3(-f_b + \beta(s)\widehat{N}_l^B + Q - \lambda^B Q)t}{\lambda^B Q^2(3Q^2t + 2Z)} \\ &+ \frac{Q(-2f_b + \beta(s)(\widehat{N}_l^A + \widehat{N}_l^B) + Q(2 - 2\lambda^B + \alpha(s)\left(\widehat{N}_b^A - \widehat{N}_b^B\right) - 3t))Z - 2Z^2}{\lambda^B Q^2(3Q^2t + 2Z)}. \end{aligned}$$

Substituting (A.16) into equations (7) and (8), we obtain the equilibrium values of N_b^i and N_l^i,

$$N_b^A = \frac{Q(\beta(s)\left(\widehat{N}_l^A - \widehat{N}_l^B\right) + Q(\alpha(s)(\widehat{N}_b^A - \widehat{N}_b^B) + 3t)) + 2Z}{6Q^3t + 4QZ} \tag{A.17}$$

$$N_b^B = \frac{Q(\beta(s)(-\widehat{N}_l^A + \widehat{N}_l^B) + Q(\alpha(s)(-\widehat{N}_b^A + \widehat{N}_b^B) + 3t)) + 2Z}{6Q^3t + 4QZ}$$

$$N_l^A = \frac{Q(\beta(s)\left(\widehat{N}_l^A - \widehat{N}_l^B\right) + Q(\alpha(s)(\widehat{N}_b^A - \widehat{N}_b^B) + 3t)) + 2Z}{6Q^2t + 4Z}$$

$$N_l^B = \frac{Q(\beta(s)(-\widehat{N}_l^A + \widehat{N}_l^B) + Q(\alpha(s)(-\widehat{N}_b^A + \widehat{N}_b^B) + 3t)) + 2Z}{6Q^2t + 4Z}$$

Here, lenders' unit transport costs t and borrowers maximum outside option value Z are sufficiently high to ensure N_b^i and N_l^i are nonnegative, regardless of the relative sizes of $\widehat{N}_l^A$ and $\widehat{N}_l^B$, and $\widehat{N}_b^A$ and $\widehat{N}_b^B$. From equation (A.16), we can derive that if and only if $Z > 2Qt$, $P_b > P_l$.

Then we provide the comparative static analysis of P_b, P_l with respect to Z. Taking the fee of Platform A as an example, we have:

$$\frac{\partial P_l^A}{\partial Z} < 0,$$

$$\frac{\partial P_b^A}{\partial Z} > 0 \; if \; and \; only \; if \; cZ^2 + 3Q^2tcZ + 3Q^2t > 0,$$

where $c = Q(\beta(s)(\widehat{N}_l^A - \widehat{N}_l^B) + \alpha(s)(\widehat{N}_b^A - \widehat{N}_b^B)Q + 3Qt)$.

If $\beta(s)(\widehat{N}_l^A - \widehat{N}_l^B) + \alpha(s)(\widehat{N}_b^A - \widehat{N}_b^B)Q \geq 0$, then since $c > 0$, we know $\frac{\partial P_b^A}{\partial Z} > 0$ for any $t, Z > 0$.

If $\beta(s)(\widehat{N}_l^A - \widehat{N}_l^B) + \alpha(s)(\widehat{N}_b^A - \widehat{N}_b^B)Q < 0$, then if $t \geq \frac{1}{3}(\beta(s)(\widehat{N}_l^B - \widehat{N}_l^A) + Q\alpha(s)(\widehat{N}_b^B - \widehat{N}_b^A))$, we have $\frac{\partial P_b^A}{\partial Z} > 0$ for any $Z > 0$.

However, if $0 < t < \frac{1}{3}(\beta(s)(\widehat{N}_l^B - \widehat{N}_l^A) + Q\alpha(s)(\widehat{N}_b^B - \widehat{N}_b^A))$, we consider the positive solution of $cZ^2 + 3Q^2tcZ + 3Q^2t = 0$, denoted as Z^*. Then $\frac{\partial P_b^A}{\partial Z} > 0$ when $Z < Z^*$ and $\frac{\partial P_b^A}{\partial Z} \leq 0$ when $Z \geq Z^*$.

In general, when platforms are symmetric, then $\frac{\partial P_b}{\partial Z} > 0$. In the case of asymmetric platforms, where one platform holds an advantage (i.e., $\beta(s)(\widehat{N}_l^A - \widehat{N}_l^B) + \alpha(s)(\widehat{N}_b^A - \widehat{N}_b^B)Q \geq 0$), the partial derivative of P_b with respect to Z for the dominant platform is also greater than zero. Since the real-world cases we can collect pertain primarily to leading platforms (i.e., dominant platforms), we focus directly on the case where $\frac{\partial P_b}{\partial Z} > 0$ in the main text.

Q.E.D.

Proof of Proposition 4

We can calculate both the lenders' and the borrowers' p-CNE on two platforms,

$$
\begin{aligned}
CNE_l^A &= \frac{\partial N_b^A}{\partial \widehat{N}_l^A} \cdot \frac{\widehat{N}_l^A}{N_b^A} = \frac{\beta(s)\widehat{N}_l^A Q}{Q(\beta(s)(\widehat{N}_l^A - \widehat{N}_l^B) + \alpha(s)(\widehat{N}_b^A - \widehat{N}_b^B)Q + 3Qt) + 2Z} \\
CNE_l^B &= \frac{\partial N_b^B}{\partial \widehat{N}_l^B} \cdot \frac{\widehat{N}_l^B}{N_b^B} = \frac{\beta(s)\widehat{N}_l^B Q}{Q(\beta(s)(-\widehat{N}_l^A + \widehat{N}_l^B) + \alpha(s)(-\widehat{N}_b^A + \widehat{N}_b^B)Q + 3Qt) + 2Z} \\
CNE_b^A &= \frac{\partial N_l^A}{\partial \widehat{N}_b^A} \cdot \frac{\widehat{N}_b^A}{N_l^A} = \frac{\alpha(s)\widehat{N}_b^A Q^2}{Q(\beta(s)(\widehat{N}_l^A - \widehat{N}_l^B) + \alpha(s)(\widehat{N}_b^A - \widehat{N}_b^B)Q + 3Qt) + 2Z} \\
CNE_b^B &= \frac{\partial N_l^B}{\partial \widehat{N}_b^B} \cdot \frac{\widehat{N}_b^B}{N_l^B} = \frac{\alpha(s)\widehat{N}_b^B Q^2}{Q(\beta(s)(-\widehat{N}_l^A + \widehat{N}_l^B) + \alpha(s)(-\widehat{N}_b^A + \widehat{N}_b^B)Q + 3Qt) + 2Z}
\end{aligned}
\tag{A.18}
$$

Calculate the first derivatives of CNE with respect to $\beta(s)$,

$$
\begin{aligned}
\frac{\partial CNE_l^A}{\partial \beta(s)} &= \frac{\widehat{N}_l^A Q(\alpha(s)\,(\widehat{N}_b^A - \widehat{N}_b^B)Q^2 + 3Q^2 t + 2Z)}{(Q(\beta(s)(\widehat{N}_l^A - \widehat{N}_l^B) + \alpha(s)(\widehat{N}_b^A - \widehat{N}_b^B)Q + 3Qt) + 2Z)^2} \\
\frac{\partial CNE_l^B}{\partial \beta(s)} &= \frac{\widehat{N}_l^B Q(\alpha(s)\,(-\widehat{N}_b^A + \widehat{N}_b^B)Q^2 + 3Q^2 t + 2Z)}{(Q(\beta(s)(\widehat{N}_l^A - \widehat{N}_l^B) + \alpha(s)(\widehat{N}_b^A - \widehat{N}_b^B)Q - 3Qt) - 2Z)^2} \\
\frac{\partial CNE_b^A}{\partial \beta(s)} &= \frac{\alpha(s)\widehat{N}_b^A(-\widehat{N}_l^A + \widehat{N}_l^B)Q^3}{(Q(\beta(s)(\widehat{N}_l^A - \widehat{N}_l^B) + \alpha(s)(\widehat{N}_b^1 - \widehat{N}_b^2)Q + 3Qt) + 2Z)^2} \\
\frac{\partial CNE_b^B}{\partial \beta(s)} &= \frac{\alpha(s)\widehat{N}_b^B(\widehat{N}_l^A - \widehat{N}_l^B)Q^3}{(Q(\beta(s)(-\widehat{N}_l^A + \widehat{N}_l^B) + \alpha(s)(-\widehat{N}_b^A + \widehat{N}_b^B)Q + 3Qt) + 2Z)^2}
\end{aligned}
\tag{A.19}
$$

since N_b^i and N_l^i in equation (A.17) are nonnegative, this implies that $\frac{\partial CNE_l^A}{\partial \beta(s)} > 0$ and $\frac{\partial CNE_l^B}{\partial \beta(s)} > 0$; the sign of $\frac{\partial CNE_b^A}{\partial \beta(s)}$ and $\frac{\partial CNE_b^B}{\partial \beta(s)}$ is determined by the relative size of $\widehat{N}_l^{\mathrm{A}}$ and $\widehat{N}_l^{\mathrm{B}}$.

Q.E.D.