Government Affiliation and Peer-to-Peer Lending Platforms in China

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JEL Classifications: G21, G28, O3.

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Abstract

With thousands of co-existing and competing platforms, the Chinese peer-to-peer (P2P) lending market experienced both high growth and high failure rate. We hand collect unique data for these P2P platforms and investigate the differences in performance and survival for platforms with and without affiliations with state-owned enterprises (SOEs). P2P platforms with SOE affiliations have higher trading volumes, attract more investors, and offer lower interest rates. These platforms also have significantly better survivability than those without the SOE affiliations, especially during market downturns. These results can be helpful to investors and regulators, especially those from other emerging markets.

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Peer-to-peer (P2P) lending, the practice of directly matching lenders and borrowers through online services, was first introduced in China in 2007. Over the past 10 years, the Chinese P2P market has enjoyed phenomenal growth and has become an important component of the financial industry. By early 2018, more than 5,000 P2P platforms had been established in China, facilitating loans in the amount of around $800 billion. This tremendous growth has been accompanied by a phenomenally high failure rate. By early 2018, over 60% of the 5,000+ P2P platforms that ever operated were closed. The substantial industry size, large cross section of platforms, and the extremely high failure rate all clearly separate the Chinese P2P market from the P2P markets from developed countries,[1] which also makes it a fascinating research subject.

One potential driver for the rapid growth of P2P platforms in China is the under-development of the economic infrastructure, including the traditional banking sector, the credit system, and the law enforcement system, which possibly leaves space for the fast growth of financial innovations such as P2P platforms. On the other hand, the under-development of the economy can also lead to many uncertainties and even systemic risks for financial innovations such as P2P platforms. In this situation, the government's guidance and regulation on the P2P platforms can be essential. Interestingly, many Chinese P2P platforms advertise prominently on their websites that they are affiliated with the government, or state-owned enterprises (SOEs), indicating that these platforms possibly believe that SOE affiliations can help them to attract potential customers. In this paper,

[1] According to *IBISWorld Industry Report OD4736: Peer-to-Peer Lending Platforms in the US, 2016,* there are around 200 platforms in the U.S. From public news coverage, three P2P platforms were closed in the U.S. As for the total transaction volumes, U.S. platforms facilitated $8.21 billion in loans in 2018, while the number for China is $178.89 billion, according to https://www.statista.com/statistics/497241/digital-market-outlook-global-comparison-alternative-lending-transaction-value, access on March 11, 2019.

we study the development and dynamics of the overall Chinese P2P market by investigating how government affiliations are related to the performance and survival dynamics of thousands of P2P lending platforms in China.

To the best of our knowledge, few if any previous studies examine the cross section of P2P platforms, possibly because there are no available public data on multiple P2P platforms. Given that the history of the industry is short, the nature of the business is private, and regulators have not requested the P2P platforms to submit their operational data, it is quite difficult to obtain relevant and direct data on multiple P2P platforms. To overcome the data difficulty, we hand collect data on thousands of P2P platforms, with substantial cross-sectional variations in government affiliations and platform performance measures. To be specific, we collect two datasets. The first dataset contains detailed weekly transaction data at the platform level for 1,593 P2P platforms from January 1, 2014 to February 28, 2018. The second dataset contains survival information for over 5,000 platforms, which covers almost all of the P2P platforms that ever existed since 2011. These novel datasets allow us to closely examine important issues such as cross-platform performance and survival, which have been difficult for previous studies to investigate. Unfortunately, P2P platforms mostly do not disclose information about individual loans, or information regarding their routine operations. Therefore, our data also do not have this detailed information.

The previous literature argues that state-owned enterprises (SOEs) could be considered government agents in China's specific setting.[2] Therefore, we use SOE affiliation as a proxy for government involvement. Our empirical results show that platforms with SOE affiliations are more likely to enjoy larger transaction volumes and attract more investors. In terms of magnitude, the transaction volumes and the number of investors for P2P platforms with SOE affiliations are on average more than double those of P2P platforms without SOE affiliations. In addition, platforms with SOE affiliations are 87.2% less likely to fail, and they offer lower interest rates by 2 percentage points. These results indicate that P2P platforms with SOE affiliations have better performance and higher survival probabilities, and SOE affiliations can serve as a signal for investors to choose among thousands of P2P platforms.

It is possible that the SOE affiliation could be correlated with unobservable variables that have nothing to do with government affiliation but affect platform performance and survival probabilities. To better understand whether the SOE affiliation itself is a good signal for selecting platforms, we examine the performance of several P2P platforms with fake SOE affiliations. That is, these platforms claim to be affiliated with SOEs, while they are not. We find that the characteristics of platforms with fake SOE affiliations resemble those of platforms without SOE affiliations, yet platforms with fake SOE affiliations attract significantly more trading volumes and investors than the other non-SOE-affiliated platforms. After the revelation of fake SOE affiliations, the performance for these platforms deteriorates significantly. The results indicate that the title of

[2] Bai, Lu, and Tao (2006) document that SOEs are charged with the task of social welfare provision by the Chinese government. Liao, Liu, and Wang (2014) document that SOEs' executives are appointed and evaluated by the Chinese government.

"SOE affiliation" itself is a valid signal for attracting more traffic for P2P platforms, even when the affiliation is fake.

What drives the relation between SOE affiliations and P2P platforms' performance? One possibility is that the SOE affiliation might provide (a perception of) government protection against defaults, even though the affiliated-SOE never gives any promises for protection. That is, if an SOE-affiliated platform were to face default, the affiliated SOE would, or is believed to, save the platform and fulfill its obligations, or at least offer better terms than the platforms without SOE affiliations. Alternatively, it could also be that P2P platforms with SOE affiliations have, or are believed to have, better access to capitals and other business resources, and enjoy higher operational efficiencies. Finally, it is also possible that, due to the affiliation with the government, the platforms are less likely to be involved in fraud or other illegal activities, or at least investors believe that to be the case. If SOE-affiliated platforms provide downside protection or offer better efficiency or have better creditability, or at least if investors believe they do, investor confidence in SOE-affiliated platforms would be bolstered. As a result, SOE-affiliated platforms have more investors, higher trading volumes and survival probabilities, and the investors are willing to accept the lower interest rates offered by them.

To thoroughly examine whether SOEs truly provide downside protection or better efficiency or better creditability for affiliated platforms, we would need detailed data on how SOEs affect day-to-day operations of the P2P platforms, how each loan performs, and whether defaulted loans are bailed out by the SOEs, while all of these data items are unavailable. As an alternative, we hand collect several platform characteristics as proxies, such as whether the affiliations are with central SOEs or local SOEs, and whether the affiliations are with financial SOEs or nonfinancial SOEs. Between central SOEs and local SOEs, the former have more creditability and resources; and between financial and nonfinancial SOEs, the former have more expertise. We find that the positive correlation between SOE affiliations and platform performance and survival are much stronger for central SOEs and financial SOEs, which sheds some light on the driving forces of the connection between SOE affiliations and platforms.

Our paper naturally connects to the growing literature on P2P lending market. This strand of literature primarily focuses on how a borrower's information (e.g., Pope and Sydnor, 2011; Duarte, Siegel, and Young, 2012; Lin, Prabhala, and Viswanathan, 2013; Iyer, Khwaja, Luttmer, and Shue, 2017) and market designs (Hildebrand, Puri, and Rocholl, 2017; Wei and Lin, 2017; Hertzber, Liberman, and Paravisini, 2018) affect lender behaviors, funding outcome, and borrower's performance. Different from our study, the above studies mostly focus on information processing using data from a single U.S. based platform. To the best of our knowledge, we are the first study to examine performance and survival across thousands of P2P lending platforms, with rich cross-sectional properties. Our paper provides a broader picture and may help investors, regulators, and practitioners better understand this blooming industry.

Recently, researchers have also studied the relation between P2P platforms and traditional financial institutions, such as commercial banks (Tang, 2019) and institutional investors (Vallee and Zeng, 2019). Many papers, such as Bartlett, Morse, Stanton, and Wallace (2018), Buchak, Matvos, Piskorski, and Seru (2018), Chen, Wu, and Yang (2018), Fuster et al. (2019), examine the advantage of fintech over traditional financial services providers. Unlike these studies, which are all based on data from developed countries, our research focuses on the largest emerging market with an under-developed banking, credit and law enforcement system, and thus provides a new perspective on how fintech firms grow and mature in an emerging market, as well as the associated benefits and costs.

Relatedly, our study is also related to the literature on how government involvement affects financial innovations. Simon (1989) argues that standard-setting by regulators can benefit participants, especially in unregulated markets, which in our case is the P2P industry. The story can also be much more complicated in emerging markets, as indicated in Glaeser, Johnson and Shleifer (2001). A recent report by the IMF, Sy et al. (2018), clearly states that "Fintech is a major force shaping the structure of the financial industry" in Africa, and "policy measures are needed to reap the potential benefits of Fintech while managing associated risks". Our analysis shows a positive correlation between P2P platforms performance and government affiliations, which provides important additional evidence to this strand of literature, and it might be particularly important for other emerging markets to design their regulations on financial innovations.

The remainder of this article is organized as follows. In Section I, we introduce the institutional background of the Chinese P2P market. Data are discussed in Section II. Section III provides the basic empirical results on the relation between government affiliation and platform performance and survival probability. We discuss the identification issue using platforms with fake

SOE affiliations in Section IV. In Section V, we provide evidence on potential channels for the positive correlation between SOE affiliations and platform performances and survivals. Section VI concludes.

I. China P2P Platforms: Institutional Background

The P2P market is first introduced in the developed markets, which have more efficient financial sectors, more mature credit score systems, and more effective law enforcement than the emerging markets do. In the existence of mature banking and investment sectors, Tang (2019) finds that the U.S. P2P market serves as a supplement to traditional banking in the case of small size loans, and as a substitute for infra-marginal bank borrowers. However, in neither case are the P2P platforms significant players in the financial market. In contrast, Chinese P2P platforms are much more important for investors and borrowers, and they play a much more significant role in society, especially for small- and medium-sized enterprises (SMEs) and individuals, whose financing needs cannot be fully satisfied by traditional financial institutions in China.

From the borrowers' side, the P2P market acts as an important alternative funding source for small firms and individuals. Due to the underdeveloped credit score system, information asymmetry, and diseconomies of scale, it is quite difficult for individuals and small firms to borrow from commercial banks. In the Chinese loan market, only 21.8% of financially constrained individuals and 46.2% of SMEs are served by the banking system.[3] The P2P market provides

[3] The former number comes from the 2010 wave of China Family Panel Studies, which was launched by the Institute of Social Science Survey (ISSS) of Peking University. The latter number comes from the 2014 wave of China Household Finance Studies, which was launched by Southwestern University of Finance and Economics.

viable access to capital for this under-served market.

From the investors' perspective, the P2P market serves as an exciting new investment channel for Chinese households. Chinese households normally consider fixed income products, stocks, mutual funds, and real estate market as investment channels. The typical annual CD rate offered by Chinese banks is approximately 3%, and the annual return on bank wealth management products is approximately 5%. The P2P lending platforms on average provide investment returns above 10%, much higher than returns offered by conventional fixed-income investment tools. In terms of stock investment and real estate investment, the recent turbulence in the Chinese stock market leads to low stock returns, and frequent regulation changes on the housing prices make real estate investments less attractive. Not surprisingly, the P2P lending platforms attract many households as a new and potentially "better" (yet riskier) investment channel, compared to traditional investments in fixed income, equity and real estate.

Given the substantial demand for this alternative capital channel and ample supply of funding, maybe it is not surprising that thousands of P2P platforms were founded over a short period to serve the market. The total transaction volume in China P2P market in 2018 reached about $178.89 billion. In comparison, the U.S. P2P platforms aggregate trading volume was $8.21 billion for the same year. By February 2018, there were more than 5,000 platforms in China, in contrast to approximately 200 in the U.S. over the same time period. The drastic difference between China and the U.S. clearly indicate the popularity and importance of P2P platforms as a funding channel in China, which is a direct result of an under-developed financial market. In addition, the large number of P2P platforms provides a rich cross section that is not observed in any other country.

P2P platforms, like many other financial innovations, can carry substantial uncertainties and risks, especially in emerging markets. They might fail, they might introduce greater fragility to the financial system, and they might even lead to systemic crises, as indicated in Carter (1989) and Rajan (2006). In the case of China's P2P industry, the rapid growth of P2P platforms has been accompanied by substantial fraud and failure. By early 2018, over 60% of P2P platforms had closed, while during the same period, only three U.S. P2P platforms are reported to have failed. We hand collect the reasons for failed Chinese P2P platforms and find that 40% of platforms were closed due to fraud, 18% of platforms were liquidated due to bad performance, while the rest ceased to exist for unknown reasons. When a platform fails, how much investors can recover varies from platform to platform, and most of the time information is not disclosed and cannot be collected on a large scale.[4]

Given the fierce cross-platform competition for visitor traffic and survival, some platforms have begun to adopt the practice of "principal guarantee"; this practice quickly has become prevalent among all P2P platforms. The "principal guarantee" means that the platform guarantees to payback principal to investors in the event of default by borrowers. Typical P2P platforms in most of the other countries, such as the U.S., only serve as an intermediary for connecting the borrowers and the lenders. When borrowers default, lenders bear the losses, which has no impact on the platform. For Chinese P2P platforms, however, when borrowers default, under "principal

[4] As an alternative, in Appendix A, we provide a couple of examples of defunct platforms, as well as how their liabilities were treated after the default.

guarantee”, the platform promises to return the principal back to the lenders. Therefore, the platform, not the lender, bears (most of) the consequence of borrowers’ default, and the majority of the credit risk exposure (at least the principal part) is shifted from individual investors to platforms.

This practice of “principal guarantee” has two important implications. First, because the platforms bear most of the default risk of individual loans, to protect the platforms from the default risk, they carefully screen the loan applications, preset the interest rates accordingly, and require collateral from borrowers if the loan amount is relatively large. Second, given that the credit risk exposure to individual loans is shifted to the platforms, and the platforms might default themselves, it is essential for investors to choose the right platform by assessing the platform’s credit-worthiness. That is, considering the under-developed credit and legal system, choosing the right platform, rather than the individual loan itself, becomes one of the most challenging and important issues for investors in the Chinese P2P market.

The Chinese government is an active and powerful participant in the financial market, and its regulation and guidance for the P2P platforms gradually evolves as the P2P market grows. The 2015 Chinese Government Work Report highlighted “entrepreneurship and innovation by all” and “financial inclusiveness”. Many of the P2P lending platforms are start-up firms, which embodies the idea of entrepreneurship. Meanwhile, the P2P platforms also serve a population with limited access to the traditional capital market, which supports the idea of “financial inclusiveness”. Given that the P2P platforms fit the government’s strategic view, the Chinese government permitted and implicitly supported the rapid growth of the P2P platforms. Before 2015, many P2P platforms were founded by state-owned enterprises, indicating that the government permits the opening of these P2P platforms.

After 2015, as frauds and scandals appeared more frequently in the media and negatively affect investors, the Chinese government took a series of correcting actions to standardize the industry. For instance, the National Internet Finance Association (NIFA) was initiated in March 2016 as an official self-regulatory organization of P2P platforms. In August 2016, the Chinese Banking and Regulatory Commission (CBRC), introduced the requirement that P2P platforms operate as information intermediaries, which prohibited them from engaging in illegal fund-raising, but without clear statements on financial or legal penalty for violations of these requirements, the cost of violation can be low.[5]

II. Data

Most existing studies on P2P platforms use data from the U.S., and they typically only examine one platform, mostly Prosper.com, which makes data publicly available. For multiple P2P platforms, because no regulation requires them to make the data publicly available, data are hard to obtain. For our study, we hand collect the data items. In Section II.A. we introduce our measure for government affiliation. The datasets for performance and survival are discussed in Section II.B. Section II.C provides summary statistics.

[5] In the Appendix B, we provide more detailed discussion on government regulations and guidance for the industry over the past four years.

A. SOE Affiliations

Following DeFond, Wong, and Li (2000), we use SOE affiliation as a proxy for government involvement. To obtain the affiliation information, we manually check all platforms' shareholder information in the National Enterprises Credit Information Publicity System, which provides public access to official registration data for all legal entities in China. A P2P platform is identified as an SOE-affiliated platform if there is one or more state-owned enterprises among the platform's shareholders, which means if tracking through the share-holding structure, one or more government agencies, central or local, is among its ultimate shareholders. Otherwise, it is identified as a non-SOE-affiliated platform. Central government agencies include all the departments of the state council, such as the State-owned Assets Supervision and Administration Commission (SASAC), and other government departments, such as the Ministry of Finance, etc. Local government agencies include, for example, the SASAC in local government, and the local Bureau of Finance.

The SOE affiliation reflects government involvement rather than government direct intervention. Typically, a SOE-affiliated platform is founded jointly by an SOE and other private entity. Notice that the SOE affiliations are established when the platforms are founded and can be changed during the life of the P2P platform. However, in our sample, there are zero cases where an SOE joins the affiliation after the platform is founded, and there are zero cases of SOE withdrawal from the affiliation after the platform is founded.

There are several reasons why SOEs choose to be affiliated with the P2P platform. It is possible that SOEs follow the nation's strategic view for "entrepreneurship" or "financial inclusiveness" and choose to be involved. It is also possible that SOEs would like to profit from this emerging P2P market. Finally, due to career concern and/or peer pressure, the leadership of SOEs might want to invest in P2P platforms so as not to miss out on this new opportunity. Without direct observable data on SOEs' intentions, we can't confirm which reason dominates, but it is likely that all reasons play some role in the P2P affiliation decision.

B. P2P Platform Performance and Survival

We use two datasets for P2P platform performance and survival. The first dataset contains weekly trading data for each platform, and we refer to this sample as the "trading sample". The data are collected from a website, www.wdzj.com, which is the largest and the most popular online information provider for P2P platforms in China. The same data have been used by regulatory authorities, such as the China Banking Regulatory Commission (CBRC), for industry overviews, we assume this sample is credible and accurately represents the P2P platform universe in China. The "trading sample" contain weekly trading data on 1,694 P2P platforms between January 1, 2014 and February 28, 2018, and data items include trading volumes, numbers of investors, terms (time to maturity), and interest rates, etc.

To ensure that our data contain the most important and liquid platforms, we apply the following filters, similar to those in Yin (2016) for hedge funds, to the weekly trading data. First, to exclude platforms with insignificant market sizes, we require each platform to have at least 5 million Chinese Yuan in registered capital. Second, to mitigate the backfill bias, we exclude the first half year of observations for each platform. Third, to eliminate reporting errors and outliers, we winsorize trading volumes, number of investors, interest rates, and registered capital at the 1st and 99th percentiles. The filtered sample contains 1,593 platforms, with 1,371 live ones and 222 defunct ones.

Our second dataset contains the life cycle information of thousands of Chinese P2P platforms, and we refer to this sample as the "long sample". As mentioned earlier, from 2011 to 2018, more than 5,000 platforms came into existence in this market, and over 3,000 platforms ended in failure. Before this study, no existing database had aggregated the information on the life cycles of these platforms. We first collect the platforms' names from www.wdzj.com, and www.p2peye.com, (the second largest online information provider for P2P platforms in China but without trading information), and then hand collect the life cycle information from the platforms' homepages and the public press. For detailed information of defunct platforms, we cross check their historical information via web.archive.org, a U.S.-based website taking snapshots of public websites automatically. The data items collected include platform name, inception date, amount of capital at time of registration, holding structure, and failure date (when applicable). We obtain information for 5,498 platforms, which covers nearly all of the P2P platforms that have existed since 2011. To exclude platforms with insignificant market sizes, we require each platform to have at least 5 million Chinese Yuan in registered capital. This filter leaves a sample of 4,210 platforms.

C. Summary Statistics on Key Variables

We present summary statistics of the pooled trading sample in Table I Panel A. In the first row, we report the mean, standard deviation and percentiles of a dummy variable *SOE*, which takes the value of one if a P2P platform is affiliated with an SOE, and zero otherwise. In our pooled trading sample, 8.9% of the platform×week observations are from platforms with SOE affiliations.

[Place Table I around here]

Next, we present summary statistics on platform performance measures. Since platform income is mostly from loan origination fees and account service fees, which are not reported but are largely based on platform transaction volumes, we use trading volumes and number of borrowers/investors as performance measures for the P2P platforms. All information is aggregated at the platform level each week, so we don't have individual loans information.

We measure *Trading Volume* as the weekly total amount of new loans funded. The mean and median values for trading volume are 29 and 4 million Chinese Yuan, respectively. For *Number of Investors*, the mean and median are 1,189 and 103 each week. The mean and median for *Numbers of Borrowers* are 289 and 5, respectively. With means significantly higher than medians, all three variables above display positive skewness. Therefore, in later empirical testing, we use the natural logarithm of the three variables. Compared to traditional loan providers, such as commercial banks, average P2P platforms are relatively small.

The trading data also provide weekly platform-level *Interest Rate*, which is computed as a loan amount-weighted average of the annualized percentage return rate of all facilitated loans for the platform during the week. The mean and median interest rates are 12.6% and 12%, respectively, which are much higher than those offered by bank deposits and wealth management products. As discussed earlier, the interest rates at Chinese P2P platforms are preset and directly offered to investors; these rates possibly reflect both the platform's risk assessment and investor's risk appetite.

For basic platform characteristics, the mean and median registered capitals of the platforms are 54 and 30 million Chinese Yuan, respectively. We later use the registered capital of a platform as a proxy for its size. We compute platform age as the number of years since inception. Our earlier data filter truncates the age variable at 26 weeks or 0.5 year. The mean and median ages of our sample observations are 2.1 and 1.9 years, indicating that the platforms are typically young and/or survive for relatively short periods of time. Another important feature of the loans is the term (time to maturity), computed as the weighted average terms of facilitated loans at the platform level during the week. The mean and median terms are 0.381 and 0.265 years, or namely, approximately 4.5 and 3 months, respectively, indicating that Chinese P2P platforms mostly facilitate short-term loans.

Table I Panel B reports the summary statistics of the long sample. The *SOE* variable has a mean of 0.031 and a median of zero, which indicates that 3.1% of the total platforms have an SOE affiliation. For other platform characteristics, P2P platforms have average registered capital of 41 million Chinese Yuan. The mean and median ages for the sample platforms are 1.793 and 1.400 years, respectively. We compute variable *defunct* as a dummy variable, taking a value of one when the platform ceases to exist as of February 2018, the ending date of data collection, and zero otherwise. We find that 2,713 platforms (64.4% of all P2P platforms) became defunct as of

February 2018, of which 16 defunct platforms are SOE-affiliated. These numbers imply that P2P lending platforms are highly risky.

III. Main Results

In this section, we examine how P2P platforms with and without SOE affiliations differ. We first study the relation between SOE affiliations and P2P performances using the trading sample in Section III.A. In Section III.B, we link a platform's affiliation to its survival in the long sample. Finally, we compare interest rates offered by P2P platforms with and without SOE affiliations using the trading sample in Section III.C.

A. SOE Affiliation and Performance

It is unclear how government affiliations are related to P2P platform performances. Rajan and Zingales (2004) state that at the early stage of a financial market, government can be useful in establishing the market rules as a central authority, which implies that the government might play a positive role in shaping financial innovation. In addition, Acharya and Kulkarni (2017) find that government affiliation can be especially important during a financial crisis, using the Indian banking system data during the 2007-2009 global financial crisis. They find that public banks had a higher deposit and credit growth than private banks, and experienced an increase in confidence, as investors believed that their downside risk was minimized because of the implicit government guarantee. Acharya and Kulkarni (2017) further note that the government guarantees facilitate state-owned banks in obtaining access to inexpensive credit and thus, state-owned banks in India outperform private sector banks during a crisis. In the context of China, Boyreau-Debray and Wei

(2005), Lu, Thangavelu and Hu (2005), Song, Storesletten and Zilibotti (2011), and Kornai (1996) determine SOEs are more likely to obtain external financing from banks and enjoy soft-budget constraints that help protect their business.

It is possible that given the potential advantages of SOEs, the SOE-affiliated platforms may attract more investors and enjoy better performances. To empirically investigate the relation between P2P performance and SOE affiliations, we use the panel data in the trading sample, and estimate the following panel regression for platform *i* at week *t*:

$$Performance_{it} = \alpha + \beta \times SOE_i + \gamma \times Control_{it} + Province_i + Week_t + \varepsilon_{it}. \qquad (1)$$

For the dependent variable, as mentioned earlier, the main source of a typical P2P platform's revenue is the origination fees charged on the facilitated loan amount on a proportionate basis, plus the service fees to investors for processing and passing on proceeds. Therefore, trading volume, number of investors, and number of borrowers directly and positively affect how much revenue a platform can collect, and we use them as performance measures. The coefficient β measures whether the SOE affiliation would affect the performance measures.

For the control variables, we follow Ackermann, McEnally and Ravenscraft's (1999) study for hedge funds and include the following three platform-level control variables: platform size, age, and the term of loans. Due to data limitations, we do not observe platform capitalization over time. Instead, we use the platform's registered capital as a proxy for *Size*. The platform's age, *Age*, is defined as the number of years since inception at time t. The term of loans on the platform, *Term*, is computed as the weighted average term of facilitated loans at the platform during the week.

For fixed effects, the ideal control would be the platform fixed effect. However, since none of the platforms changed their affiliations in the sample, the platform fixed effect won't be identifiable from the SOE coefficient. Instead, we control for location fixed effect and time fixed effect. The location fixed effect, $Province$, is defined as where a platform's headquarter is located, which can be any of the 31 provinces (except for Hong Kong, Macau, and Taiwan). The location fixed effect accounts for time-invariant systematic differences across provinces, such as legal environment, local banking market, local tax difference, and local governments' strategic plans. Variable $Week$ represents time fixed effects by week, such as seasonality, the business cycle, regulations change, and trends in P2P lending over time. We double cluster standard errors at both the platform level and the week level, because the performance for a given platform may be correlated over time, and performance across the platforms for a given time may be correlated as well.

[Place Table II around here]

Table II reports the estimation results on how SOE affiliation is related to our three performance measures. In the first regression for trading volume, the coefficient on SOE is 0.775 with a t-statistic of 6.146. In other words, an SOE-affiliated platform has 117.06% $(= \mathrm{e}^{0.775} - 1)$ more trading volume on average than a non-SOE-affiliated platform. In the second regression for number of investors, the coefficient on SOE is 0.814, with a significant t-statistic of 4.192. Economically, a SOE-affiliated platform attracts 125.69% $(= \mathrm{e}^{0.814} - 1)$ more investors than a non-SOE-affiliated platform does on average. For the third regression for number of borrowers, the coefficient on SOE is 0.178, with an insignificant t-statistic of 1.056. In terms of magnitude, an SOE-affiliated platform has 19.48% ($= \mathrm{e}^{0.178} - 1$) more borrowers than a non-SOE-affiliated platform on average.

It is perhaps not surprising that the SOE affiliation is more important for investors than borrowers. For investors, given the principal payback guarantee by platforms, it is more important to evaluate the default risk of the platforms rather than the default risk of the loans. The SOE affiliation possibly provides useful information for investors to choose platforms, which is why the SOE affiliation is important for explaining the number of investors. For borrowers, however, because the platforms bear most of the credit risks from the borrowers, given the principal payback guarantee, the platforms are highly cautious in selecting the loans. The procedures adopted by the SOE-affiliated platforms may not vary substantially from the non-SOE-affiliated platforms, and therefore, the SOE affiliation does not significantly affect the number of borrowers. In future tables, we most focus our discussion on number of investors rather than number of borrowers.

The coefficients on the control variables are all significant and carry the expected signs. Larger platforms and older platforms tend to have higher trading volumes and attract more investors and borrowers. Interestingly, platforms with longer term loans tend to attract more traffic. The R^2s for all three regressions are approximately 25%. Our findings in Table II show that platforms with SOE affiliations are more likely to attract higher trading volumes, more investors, and more borrowers. [6]

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[6] We conduct two robustness checks, and results are reported in Appendix C. First, to better control for size, we match

B. SOE Affiliation and Survival

We examine P2P platforms survivals using the long sample, with 4,210 platforms. Since the survival variables are right-censored at the sample collection date, we follow Kiefer (1988) and Seru, Shumway, and Stoffman (2010), and use the Cox model to estimate the effect of SOE affiliation on P2P platforms' survival probability. At the end of February 2018, we estimate the following specification,

$$h_i(t) = h_0(t)\exp(\delta \times SOE_i + \gamma \times Control_i + Province_i), \tag{2}$$

where the hazard rate, $h_i(t)$, is platform *i*'s probability of failing at time *t* conditioning on not failing until time *t*, and $h_0(t)$ is the baseline hazard function at time zero. The coefficient δ measures how much the SOE affiliation would affect the change in the hazard rate each period. A negative estimate of δ implies that SOE platforms are less likely to fail than a non-SOE platform. For control variables, we include platform size and province fixed effect. We do not include platform age or week fixed effect, because the Cox analysis has already accounted for the duration that the platform has been in existence. We also do not include term as a control variable, because the data are unavailable in the long sample.

We report the Cox analysis results in Table III. The coefficient on the *SOE* variable is -2.055, with a significant t-statistic of -8.172, with the standard errors clustered by platform as in Heimer (2016). The negative sign indicates that SOE affiliation significantly reduces the conditional

each SOE affiliated platform with three similar-sized platforms without SOE affiliation, and re-estimate the panel regression. Second, we use monthly data rather than weekly data. The results are quite similar to those in Tables 2, 3 and 4. In both cases, SOE-affiliated platforms have higher trading volume, number of investors, and survival probability and lower interest rates than non-SOE-affiliated platforms.

default probability of P2P platforms. In economic terms, the hazard ratio of $0.128 = \exp(-2.055)$ indicates that during the sample period (from 2014 to Feb 2018), the conditional failure probability for P2P platforms with SOE affiliation is only 12.8% of that for P2P platforms without SOE affiliation. In other words, P2P platforms with SOE affiliation are, on average, 87.2% less likely to default than those without SOE affiliation. The coefficients on the size variable is negative and significant, indicating that larger platforms survive longer.

[Place Table III around here]

As in Acharya and Kulkarni (2017), government affiliation can be especially important during financial crises. If the investors believe that the SOEs would protect the affiliated P2P platforms from failing, they would not abandon the SOE-affiliated platforms, and these platforms are more likely to survive. The recent Chinese stock market turbulence over year 2014 and 2015 provide an excellent opportunity to investigate the survival pattern of the P2P platforms. Between June 2014 and June 2015, the Shanghai Stock Exchange Composite Index (SSECI) first surged by approximately 110%. In early July 2015, however, the SSECI plummeted by 32%, destroying more than 18 trillion Chinese Yuan in share value, according to Huang, Miao, and Wang (2016). On August 24, 2015, the SSECI fell by another 8.48%, marking the largest single day fall since 2007. From October 2015 to the end of our sample, the market slowly recovered.

We directly investigate the defunct probabilities of various P2P platforms from June 2015 to June 2016. In this exercise, we require the platforms to be founded before January 1, 2015 to have an adequate number of time series observations for each platform when market turbulence occurs.

Our sample contains 1,754 platforms, of which 77 are SOE-affiliated. As of June 2016, 773 platforms, or 44.1% of all platforms in this sample, ceased to exist, yet *none* of these 773 defunct platforms are affiliated with SOEs. This distinctive pattern provides strong evidence that SOE-affiliated platforms are much less likely to default than non-SOE platforms during market turmoil.

C. SOE Affiliation and Interest Rate

Interest rates are key variables for P2P loans. As discussed earlier, most P2P platforms provide principal guarantee, and bear most of the default risks from borrowers. As a result, the P2P platforms preset the interest rates for investors. If SOE affiliation is associated with higher platform survival probability, maybe it is natural that investors are willing to accept lower interest rates for SOE-affiliated platforms. Therefore, we use the trading sample to estimate the following specification for platform *i* at week *t*:

$$InterestRate_{it} = \alpha + \beta \times SOE_i + \gamma \times Control_{it} + Province_i + Week_t + \varepsilon_{it} \ . \tag{3}$$

Table IV presents the estimated coefficients. The coefficient on SOE is -2.134 with a t-statistics of -6.925, suggesting that the interest rates offered by a SOE-affiliated platform on average are 2.134% lower than that by a non-SOE-affiliated platform.

[Place Table IV around here]

Our finding that SOE-affiliated platforms offer lower interest rates to investors is close to findings in Allen, Gu, Qian, and Qian (2017), which examine Chinese trust products and find that if the products are issued by trust companies affiliated with SOEs, then the yield spreads are significantly lower. They conclude that the expectation of an implicit protection from the government affects the pricing.[7]

IV. Identification: Fake SOE Affiliation

In the previous sections, we provide empirical evidence that P2P platforms with SOE affiliations have higher trading volumes and higher survival probabilities. Nevertheless, it is possible that SOE affiliation could be correlated with some unobservable variables that affect platforms' performance and survival probabilities. In this section, we investigate this identification issue by using data from platforms with fake SOE affiliations. Session IV.A compares the performance of platforms with fake SOE affiliations and other platforms. Section IV.B discusses how the revelation of the fake SOE affiliations affects platform performance.

A. Fake SOE Affiliation and Platform Performance

We identify platforms with fake SOE affiliations in two steps. First, with the registration information, we clarify that these platforms do not have SOEs as an ultimate shareholder and do not have real connections with SOEs. Second, the platforms publicly advertise that they have SOE affiliations. For example, Jucaivoo.com, originally claimed on its website and advertisements that it was affiliated with China National Nuclear Corporation (CNNC), a large state-owned enterprise under direct management by the Chinese central government. However, on February 7, 2018, CNNC announced that it never had any relations with any P2P platforms, and CNNC would not bear the consequences of any actions taken by any P2P platform.

[7] In Appendix D, we examine a small sample provided by NIFA on member P2P platforms on their financial performances. We find no statistically significant differences in the profitability between P2P platforms with and without SOE affiliations.

We are able to identify eleven platforms with fake affiliations with CNNC, consisting of 1,499 observations in the trading sample, equivalent to over 13% of real SOE affiliated platforms observations. We define *FakeSOE* as a dummy variable, taking the value of one when a platform fakes its SOE affiliation, and zero otherwise.

We first compare platforms with fake SOE affiliations to other platforms. From Panel A of Table V, we find that the platforms with fake SOE affiliations are significantly smaller than platforms with true SOE affiliations and are not significantly different from platforms without SOE affiliations. Interestingly, platforms with fake SOE affiliations survive longer, by a few months, than platforms with true SOE affiliations and no SOE affiliations.

[Place Table V around here]

Next, we investigate whether fake SOE affiliations attract more traffic than platforms with no SOE affiliations. Following Chemmanur, Loutskina, and Tian (2014), for each fake-SOE-affiliated platform, we match it with three control platform with similar size, age and province at the beginning of the sample. Based on the matched sample, we estimate the following specification:

$$Performance_{it} = \alpha + \beta \times FakeSOE_i + Week_t + \varepsilon_{it}. \quad (4)$$

We restrict the sample to the week before the revelation. In the first regression for trading volume of Table V Panel B, the coefficient on $FakeSOE$ is 0.740 with a t-statistic of 2.237. In other words, a platform with fake SOE affiliation on average has 109.59% ($= \mathrm{e}^{0.740} - 1$) more trading volume than matched non-SOE-affiliated platforms do. In the second regression for number of investors, the coefficient on $FakeSOE$ is 1.135, with a significant t-statistic of 2.123.

Economically, a fake-SOE-affiliated platform attracts 211.12% ($= \mathrm{e}^{1.135} - 1$) more investors than other non-SOE platforms do on average. The above results suggest that the title of "SOE affiliation" itself could attract more traffic for P2P platforms, even though it is fake.

We also use the matched sample to compare survival probabilities for platforms with fake SOE affiliations. Since no platforms with fake SOE affiliations failed during the sample period, the cox model can't be identified, we estimate the following probit model,

$$\Pr(Defunct_{it}) = \Phi(\alpha + \beta \times FakeSOE_i + Week_t + \varepsilon_{it}). \quad (5)$$

Here, we construct a platform×week panel data using the long sample, and $Defunct_{it}$ is a dummy variable equal to one if a platform *i* is defunct during week *t*, and zero otherwise.

From the last column in Table V Panel B, for convenience of economic interpretation, we report marginal effect of *FakeSOE*, which is -3.837% with a significant t-statistic of -18.893. That is, the P2P platforms with fake SOE affiliations have a weekly failure rate that is 3.837% (or an annual failure rate that is 86.93%=1-(1-3.837%)^{52}) less than that of other non-SOE-affiliated P2P platforms. In other words, the platforms with fake SOE affiliations are significantly more likely to survive than other platforms with no SOE affiliations.

B. Revelation of Fake SOE Affiliations

What happens after the fake SOE affiliations are revealed? We examine the *revelation* of fake SOE affiliations on February 7, 2018 to see how the platform performance changed afterwards. If SOE affiliation is a valid signal for market participants, then when the fake signal is corrected, we expect to see the market self-adjust to the new information, and the performance measures for platforms with fake SOE affiliations would deteriorate.

We construct a dummy variable, *After*, with value of one after the fake SOE affiliations are revealed, and zero otherwise. We estimate the following specification,

$$Performance_{it} = \alpha + \beta_1 \times After_i \times FakeSOE_i + \beta_2 \times FakeSOE_i + \beta_3 \times After_i + \varepsilon_{it}. \quad (6)$$

The interaction term, $After_i \times FakeSOE_i$, captures the difference-in-difference effect. The regressions are estimated using the same one-to-three matched sample of platforms with fake and no SOE affiliations in the previous subsection. Since we only have three weeks of data after the revelation, the related coefficient estimates might have large standard errors.

Panel C of Table V compares the performance measures of platforms with no or fake SOE affiliations before and after the fake SOE affiliation revelation.[8] For trading volume and number of investors, the coefficients on interaction terms between *FakeSOE* and *After* are both significantly negative, implying that platforms with fake SOE affiliations are more negatively affected by revelation than other non-SOE-affiliated platforms. As expected, the coefficients on *FakeSOE* are positive and significant, indicating that a fake SOE affiliation is associated with better traffic. When we consider the magnitude of the coefficients for *FakeSOE* and $FakeSOE \times After$ together, the original positive coefficients on *FakeSOE* is mostly offset by the negative coefficients on the interaction term, indicating that platforms with fake SOE affiliations become

[8] To show that the effects on fake SOEs differ significantly before and after the revelation, we present a trend chart in Appendix E. The two lines representing the natural logarithm of trading volume (number of investors) for the fake-SOE-affiliated platforms and non-SOE-affiliated platforms trend closely in parallel in the six weeks leading up to the revelation of fake SOE affiliations. On the revelation and afterwards, the line for the non-SOE-affiliated platforms start to climb and the line for the fake-SOE-affiliated platforms start to decline and two lines start to converge, indicating different pattern in performances for two groups and a drop for the fake-SOE-affiliated platforms. The results clearly show that the revelation event, rather than other time trend, affects the results.

no different from other non-SOE-affiliated platforms after the fake information was revealed.

Overall, the results in Table V indicate that compared to other non-SOE platforms, the performance measures for fake-SOE-affiliated platforms are better before revelation of fake status, but worse afterwards. This result indicates that the SOE affiliation itself, rather than some unobservable variables, is a valid signal for investors to choose platforms.

V. Possible Channels

Why would SOE affiliation be positively related to platform performance and survival? It is possible that SOE affiliations provide, or are perceived to provide, protection against platform default, better operational efficiencies, and/or better creditability. Since we do not directly observe the interactions between the SOEs and the P2P platforms, we cannot provide direct answers. In this section, we consider variables that could potentially affect the relation between SOE affiliation and platform performance and survival, which could shed some light on the underlying channels and mechanisms of the relation. In Section V.A, we separate the SOEs into central SOEs and local SOEs. In Section V.B, we separate the platforms into financial SOEs and nonfinancial SOEs.

A. Central vs. Local SOEs

Chen, Démurger and Fournier (2005) suggest that central SOEs often enjoy higher creditability than local SOEs, due to their higher ability to protect their stakeholders. In our case, if there is a protection from the SOEs, or if there is belief that there is a protection, we expect P2P platforms affiliated with central SOEs are more likely to perform better than platforms affiliated with local SOEs because the potential protection is more trustworthy from central SOEs.

To examine the difference between the central SOEs and noncentral SOEs, we estimate the following specification:

$$Performance_{it} = \alpha + \beta \times CentralSOE_i + \theta \times NCentralSOE_i + \gamma \times Control_{it} + \ Province_i + Week_t + \varepsilon_{it} \ , \qquad (7)$$

where *CentralSOE* is a dummy variable, which equals one if the State Council (the central government) is one of the ultimate shareholders of the P2P platform, and zero otherwise. Variable *NCentralSOE* is also a dummy variable, which is equal to one if the platform is only affiliated with noncentral SOE(s), and zero otherwise. Among the 114 SOE-affiliated platforms in the trading sample, 31 platforms are affiliated with central SOE(s). In Table VI Panel A, for performance measures, the coefficients on *CentralSOE* and *NCentralSOE* are all positive, and the former are generally larger than the latter. In the fourth regression for interest rates, all SOE-affiliated platforms offer significantly lower interest rates to investors than non-SOE-affiliated platforms with similar magnitudes. That is, while both types of SOE-affiliated platforms attract more trading volumes and investors than non-SOE-affiliated platforms, the central-SOE-affiliated platforms do better than the local-SOE-affiliated platforms.

[Place Table VI around here]

We also expect platforms affiliated with central SOEs are less likely to default than those affiliated with local SOEs. Using the long sample, we estimate the following equation:

$$\Pr(Defunct_{it}) \ = \Phi(\alpha + \beta \times CentralSOE_i + \theta \times NCentralSOE_i + \gamma \times Control_{it} + Province_i + Week_t + \varepsilon_{it}). \qquad (8)$$

The fifth column in Table VI Panel A shows that the marginal effect on *CentralSOE* and *NCentralSOE* are -3.541% and -0.693%, respectively. In economic terms, the P2P platforms affiliated with central SOEs have a weekly failure rate that is 3.541% less than that of non-SOE-affiliated P2P platforms, while the number for platforms with local SOEs is 0.693%. That is, P2P platforms affiliated with central SOEs have higher trading volumes, more investors, and higher survival probabilities than those affiliated with local SOEs, possibly because they have better creditability and they provide or are perceived to provide downside protections for the affiliated platforms.

B. Financial vs. Non-Financial SOEs

Compared to nonfinancial institutions, financial institutions have more relevant expertise, more connections in their business network, and more financing capacity, and the affiliated P2P platforms are more likely to perform better than non-affiliated P2P platforms. To examine the difference between the impacts of financial SOEs and nonfinancial SOEs, we estimate the following specification:

$$Performance_{it} = \alpha + \beta \times FinSOE_i + \theta \times NFinSOE_i + \gamma \times Control_{it} + \quad Province_i$$
$$+Week_t + \varepsilon_{it} \quad , \tag{9}$$

where *FinSOE* is a dummy variable, taking a value of one for a platform if it is affiliated with an SOE running a financial business, such as an insurance company, a mutual fund company, or an asset management company, and zero otherwise. Variable *NFinSOE* is equal to one if the platform is only affiliated with nonfinancial SOE(s) and zero otherwise. Among the total 114 SOE platforms in the trading sample, there are 21 with financial SOE affiliations.

In Panel B of Table VI, the coefficients on *FinSOE* and *NFinSOE* for trading volume, number of investors, number of borrowers, and interest rates all carry the expected signs and almost all are statistically significant. Interestingly, the magnitudes of the coefficients are always larger for *FinSOE* than for *NFinSOE*. When we compare whether the differences between the financial and nonfinancial SOE coefficients are significant, we find that they are significant in most cases. We also estimate the survival probability for these two types of SOE affiliations, with a similar specification as in equation (8). From the fifth column in Table VI Panel B, the coefficient on *FinSOE* and *NFinSOE* are both negative, and the marginal effect is significantly larger for *FinSOE* than that for *NFinSOE*.

The results suggest that platforms with financial SOE affiliations have better performances and survive better than platforms with nonfinancial SOE affiliations. Possibly, the financial SOE affiliations provide more expertise, better networks, and more access to the capital market. This is slightly different from the trustworthiness and the protection for default risk mentioned earlier, but these perspectives are not mutually exclusive, and they can all be at work.

VI. Conclusion

For the past few years, P2P platforms have thrived in China and have provided an alternative, yet important, funding/investment channel. Unlike the P2P platforms in other countries, China's P2P platforms have many unique and interesting features, such as government involvement, guarantee on principals, and a large cross section of competing P2P platforms, all of which makes the P2P industry an interesting research topic.

In this paper, we examine the cross section of P2P platforms, and how platform performance differs with and without government affiliations. Using unique, hand-collected platform-level data, we present a few interesting empirical findings. First, P2P platforms affiliated with SOEs have higher trading volumes and attract more investors. Second, P2P platforms with SOE affiliations have higher survival probabilities, especially during the 2015-2016 Chinese stock market downturns. Third, the interest rate offered by SOE-affiliated platforms are significantly lower than other platforms. Finally, using P2P platforms with fake SOE affiliations, we show that the SOE affiliation itself is an important signal for P2P market participants. These findings have direct implications for investors in choosing among thousands of P2P platforms by using SOE affiliation as a signal.

Our study also has important implications for regulators. Clearly, governments play an important role in global financial markets. However, in terms of how governments influence financial development, the answers vary from one country to another. Our paper focuses on the Chinese P2P lending market, a significant component of the rising fintech industry. We provide evidence that government affiliation has positive correlations with performance measures in the fintech industry, which might be useful for other emerging markets aiming to develop a fintech industry.

References

Acharya, V. V., N. Kulkarni, 2017, Government Guarantees and Bank Vulnerability During the Financial Crisis of 2007–09: Evidence from an Emerging Market. Working Paper. NYU Stern School of Business.

Ackermann, C., R. McEnally, D. Ravenscraft, 1999, The Performance of Hedge Funds: Risk, Return, and Incentives, *Journal of Finance* 54, 833-874.

Allen, F., X. Gu, J. Qian, and Y. Qian, 2017, Implicit Guarantee and Shadow Banking: The Case of Trust Products.

Bai, C., J. Lu, Z. Tao, 2006, The Multitask Theory of State Enterprise Reform: Empirical Evidence from China, *American Economic Review Papers and Proceedings* 96, 353-357.

Bartlett, R., A. Morse, R. Stanton, N. Wallace, 2018, Consumer-Lending Discrimination in the Era of FinTech, Available at SSRN: https://ssrn.com/abstract=3063448.

Boyreau-Debray, G., S. J. Wei, 2005, Pitfalls of a State-Dominated Financial System: The Case of China, National Bureau of Economic Research, No. w11214.

Brown, J., J. Huang, 2017, All the President's Friends: Political Access and Firm Value, NBER working paper 23356.

Buchak, G., G. Matvos, T. Piskorski, and A. Seru, 2018, Fintech, regulatory arbitrage, and the rise of shadow banks, *Journal of Financial Economics* 130, 453–483.

Carter, M., 1989, Financial Innovation and Financial Fragility, *Journal of Economic Issues* 23, 779-793.

Chemmanur, T. J., E. Loutskina, X. Tian, 2014, Corporate Venture Capital, Value Creation, and Innovation, *Review of Financial Studies* 27, 2434-2473

Chen, Y., S. Démurger, M. Fournier, 2005, Earnings Differentials and Ownership Structure in Chinese Enterprises, *Economic Development and Cultural Change* 53, 933-958.

Chen, M., Q. Wu, B. Yang, 2018, How Valuable is FinTech Innovation (with Mark Chen and Qinxi Wu), *The Review of Financial Studies*, *forthcoming.*

DeFond, M. L., T. J. Wong, S. Li, 2000, The Impact of Improved Auditor Independence on Audit Market Concentration in China, *Journal of Accounting and Economics* 28, 269-305.

Duarte, J., S. Siegel, L. Young, 2012, Trust and Credit: The Role of Appearance in Peer-to-Peer Lending, *The Review of Financial Studies* 25, 2455-2484.

Fuster, A., M. C. Plosser, P. Schnabl, and J. Vickery, 2019, The Role of Technology in Mortgage Lending, *The Review of Financial Studies* 32, 1854-1899.

Glaeser, E., S. Johnson, A. Shleifer, 2001, Coase versus the Coasians, *The Quarterly Journal of Economics* 116, 853-899.

Hildebrand, T., M. Puri, J. Rocholl, 2017, Adverse Incentives in Crowdfunding, *Management Science* 63, 587-608.

Heimer, R., 2016, Peer Pressure: Social Interaction and the Disposition Effect, *Review of Financial Studies* 29, 3177–3209.

Huang, Y., J. Miao, P. Wang, 2016, Saving China's Stock Market, Available at SSRN: https://ssrn.com/abstract=2821664.

Iyer, R., A. I. Khwaja, E. F. Luttmer, K. Shue, 2015, Screening Peers Softly: Inferring the Quality of Small Borrowers, *Management Science* 62, 1554-1577.

Kiefer, N., 1988, Economic Duration Data and Hazard Functions, *Journal of Economic Literature* 26, 646-679.

Kornai, J., 1986, The Soft Budget Constraint, *Kyklos* 39, 3-30.

Liao, L., B. Liu, H. Wang, 2014, China's Secondary Privatization: Perspectives from the Split-Share Structure Reform, *Journal of Financial Economics* 113, 500-518.

Lin, M., N. R. Prabhala, S. Viswanathan, 2013, Judging Borrowers by the Company they Keep: Friendship Networks and Information Asymmetry in Online Peer-to-Peer Lending, *Management Science* 59, 17-35.

Lu, D., S. M. Thangavelu, Q. Hu, 2005, Biased Lending and Non-Performing Loans in China's Banking Sector, *Journal of Development Studies* 41, 1071-1091.

Pope, D., J. Sydnor, 2011, What's in a Picture? Evidence of Discrimination from Prosper.com, *Journal of Human Resources*, 46(1), 53-92.

Rajan, R. G., 2006, Has Finance Made the World Riskier? *European Financial Management* 12, 499-533.

Rajan, R. G., L. Zingales, 2004, Saving Capitalism from the Capitalists: Unleashing the Power of Financial Markets to Create Wealth and Spread Opportunity, Princeton University Press.

Seru, A., T. Shumway, N. Stoffman, 2010, Learning by Trading, *Review of Financial Studies* 23, 705-739.

Simon, C., 1989, The Effect of the 1933 Securities Act on Investor Information and the Performance of New Issues, *American Economic Review*, 79(3), 295-318.

Song, Z., K. Storesletten, F. Zilibotti, 2011, Growing like China, *The American Economic Review* 101, 196-233.

Sy, A., R. Maino, A. Massara, H. P. Saiz, and P. Sharma, 2018, FinTech in Sub-Saharan African Countries : A Game Changer? Departmental Paper No. 19/04, available at https://www.imf.org/en/Publications/Departmental-Papers-Policy-Papers/Issues/2019/02/13/FinTech-in-Sub-Saharan-African-Countries-A-Game-Changer-46376.

Tang, H., 2019, Peer-to-Peer Lenders versus Banks: Substitutes or Complements? *The Review of Financial Studies* 32, 1900-1938.

Vallee, B., Y. Zeng, 2019, Marketplace Lending: A New Banking Paradigm? *The Review of Financial Studies 32*, 1939-1982.

Wei, Z., M. Lin, 2017, Market Mechanisms in Online Peer-to-Peer Lending, *Management Science* 63, 4236-4257.

Yin, C., 2016, The Optimal Size of Hedge Funds: Conflict between Investors and Fund Managers. *The Journal of Finance* 71 (4), 1857–1894..

Table I

P2P Platforms Features Summary Statistics

This table presents the summary statistics for the features of P2P platforms using two samples. Panel A and B present the summary statistics of the trading sample and the long sample respectively. Panel A presents summary statistics for the trading sample when we pool all platform-week observations together. The data are collected from www.wdzj.com. The sample period is from January 2014 to February 2018. *SOE* is a dummy variable with a value of one for platforms affiliated with SOEs and zero otherwise. *Trading Volume* is the total funding facilitated by the platform. *Number of Investors* is the number of investors on the platform. *Number of Borrowers* is the number of borrowers on the platform. *Interest Rate (%)* is the weighted annualized percentage rate of the platform loans weighted by each loan amount, which is offered to investors. *Size* is measured by the registered capital of the platform. *Age* is the number of years the platform *i* has been in operation since its inception till time *t*. *Term* is the weighted average term of loans from the platform weighted by each loan amount. Panel B presents summary statistics for the features of P2P platforms in the long sample. The long sample consists of P2P platforms that existed from 2011 to February 2018 in China. The data are collected manually from www.wdzj.com, www.p2peye.com, and web.archive.org. We require each platform to have at least 5 million CNY in registered capital. *Size* is measured by the registered capital of the platform. For living platforms, *Age* is the number of years the platform has been in operation between its inception and the end of February 2018; For dead platforms, *Age* is the number of years between its inception and failure. *Defunct* is a dummy variable taking a value of one for platforms ceasing to exist and zero for surviving platforms as of February 2018.

Panel A. Trading Sample (N=128,673)

	Mean	Std. Dev.	P1	P25	P50	P75	P99
SOE	0.089	0.284	0	0	0	0	1
Y variables							
Trading Volume (million CNY)	29.048	76.743	0.047	1.3	4.474	17.251	535.741
Number of Investors	1189.420	4062.200	0	28	103	491	30083
Number of Borrowers	289.250	1556.450	1	1	5	23	12949
Interest Rate (%)	12.604	4.444	5.78	9.54	11.93	14.7	31
Control variables							
Size / Registered Capital (million CNY)	54.034	92.029	5	10	30	50.01	770
Age (years)	2.094	1.183	0.534	1.236	1.910	2.704	6.214
Term (years)	0.381	0.379	0.034	0.159	0.265	0.47	2.427

Panel B. Long sample (N=4,210)

	Mean	Std. Dev.	P1	P25	Median	P75	P99
SOE	0.031	0.173	0	0	0	0	1
Size / Registered Capital (million CNY)	41.386	48.459	5	10	30	50	300
Age (years)	1.793	1.400	0.005	0.063	1.475	2.912	5.186
Defunct	0.644	0.479	0	0	1	1	1

Table II

P2P Platform Performance and SOE Affiliation

This table presents the results of the ordinary least squares regression for our baseline model (1). The data are collected from www.wdzj.com. The sample period is from January 2014 to February 2018. *Trading Volume* is the total funding facilitated on the platform. *Number of Investors* is number of investors on the platform. *Number of Borrowers* is number of borrowers on the platform. *SOE* is a dummy variable with a value of one for platforms affiliated with SOEs and zero otherwise. *Size* is measured by the registered capital of the platform. *Age* is the number of years since the platform i's inception to time t. *Term* is the weighted average term of loans from the platform weighted by each loan amount. In all regressions, province fixed effects and week fixed effects are included. Standard errors are clustered at both the platform and the week level. T-statistics are reported in parentheses. *** indicates the coefficient is different from zero at the 1% level, ** at the 5% level, and *at the 10% level.

	(1)	(2)	(3)
	Ln(Trading Volume)	Ln(# Investors)	Ln(# Borrowers)
SOE	0.775***	0.814***	0.178
	(6.146)	(4.192)	(1.056)
Ln(Size)	0.260***	0.367***	0.245***
	(7.237)	(6.635)	(5.118)
Ln(Age)	1.163***	1.857***	1.786***
	(7.966)	(8.868)	(7.708)
Ln(Term)	0.855***	0.852***	2.123***
	(5.211)	(3.045)	(7.484)
Province FE	Y	Y	Y
Week FE	Y	Y	Y
Observations	128,673	128,673	128,673
R-squared	0.284	0.217	0.272

Table III
SOE Affiliation and Survival: Cox model

This table presents the estimates of determinants of the hazard rate to becoming a defunct platform using the Cox-proportional hazard model (2). *SOE* is a dummy variable with a value of one for platforms affiliated with SOEs and zero otherwise. *Size* is measured by the registered capital of the platform. Province fixed effects is included. T-statistics are reported in parentheses. *** indicates the coefficient is different from zero at the 1% level.

	Cox analysis	
	Coefficient	Hazard ratio
SOE	-2.055***	[0.128]
	(-8.172)	
Ln(Size)	-0.137***	
	(-6.819)	
Province FE	Y	
Observations	4,210	

Table IV

P2P Platform Interest Rate and SOE Affiliation

This table presents the results from the ordinary least squares regression of model (3). The data are collected from www.wdzj.com. The sample period is from January 2014 to February 2018. *Interest Rate (%)* is the weighted annualized percentage rate of the platform loans weighted by each loan amount, which is offered to investors. *SOE* is a dummy variable with a value of one for platforms affiliated with SOEs and zero otherwise. *Size* is measured by the registered capital of the platform. *Age* is the number of years since the platform's inception. *Term* is the weighted average term of loans of the platform by each loan amount. Province fixed effects and week fixed effects are included. Standard errors are clustered at both the platform and the week level. T-statistics are reported in parentheses. *** indicates the coefficient is different from zero at the 1% level, ** at the 5% level, and * at the 10% level.

	Interest Rate (%)
SOE	-2.134***
	(-6.925)
Ln(Size)	-0.308***
	(-3.349)
Ln(Age)	0.680**
	(2.194)
Ln(Term)	-1.203***
	(-3.044)
Province FE	Y
Week FE	Y
Observations	128,673
R-squared	0.275

Table V
Fake SOE Affiliation and Platform Performance

This table presents the ordinary least squares estimation results on performance measures, interest rates, and survivals for platforms with fake SOE affiliations. The data are collected from www.wdzj.com. The sample period is from January 2014 to February 2018. Panel A compares the summary statistics for platforms with fake SOE affiliations and other platforms. In Panel B, we match each fake-SOE-affiliated platform with three non-SOE-affiliated platforms with similar size, age and the same province, respectively, and examine the performance for fake SOE affiliations vs. non-SOE affiliations based on the matched samples using model (4). Panel B also presents the marginal effect for platform failure probabilities using model (5); Panel C presents the ordinary least squares estimation results using fake SOE affiliation revelation as a shock. *FakeSOE* equals one if the platform has a fake SOE affiliation and zero otherwise. *After* is a dummy variable equal to one when the fake SOE affiliations are revealed and zero otherwise. Standard errors are clustered at the platform and the week level in Panel B Column (1) and (2) and Panel C. T-statistics are reported in parentheses. *** indicates the coefficient is different from zero at the 1% level, ** at the 5% level, and * at the 10% level.

Panel A. Summary Statistics for Platforms with Fake SOE Affiliations

	(1)	(2)	(3)	(4)	(5)
	Fake SOE Platforms	SOE Platforms	Non-SOE Platforms	p-value for diff. (2)-(1)	p-value for diff. (3)-(1)
Registered Capital (million CNY)	51.526	62.917	53.247	0.000***	0.238
Age (years)	2.594	2.225	2.074	0.000***	0.000***
Term (years)	0.380	0.460	0.374	0.000***	0.247

Panel B. Fake SOE Affiliation vs. Non SOE Affiliation, Matched Sample

	(1)	(2)	(3)
	Ln(Trading Volume)	Ln(#Investors)	Platform Failure Probability
FakeSOE	0.740**	1.135**	-3.837%***
	(2.237)	(2.123)	(-18.893)
Week FE	Y	Y	Y
Observations	4,612	4,612	6,323
R-squared	0.168	0.097	0.502

Panel C. Revelation of Fake SOE Affiliation and Platform Performance, Matched Sample

	(1)	(2)
	Ln(Trading Volume)	Ln(#Investors)
FakeSOE	0.728**	1.103**
	(2.195)	(2.048)
FakeSOE×After	-0.806***	-0.757*
	(-4.648)	(-1.829)
After	0.554***	0.283
	(4.542)	(0.768)
Observations	4,764	4,764
R-squared	0.205	0.177

Table VI
Potential Channels

This table presents the estimation results relating platform performances and survivals to platforms affiliated with certain types of SOEs. Panel A presents the estimations for performance measures and interest rates for platforms affiliated with central SOEs vs. those with noncentral SOEs using model (7) and presents the marginal effect for platform failure probabilities in Column (5) using model (8). *CentralSOE* is equal to one if the State Council (the central government) is one of the ultimate shareholders of the P2P platform, and zero otherwise. *NCentralSOE* is equal to one if the platform is only affiliated with noncentral SOE(s) and zero otherwise. Panel B presents the estimations for performance measures and interest rates for platforms affiliated with financial SOEs vs. those with nonfinancial SOEs using model (9), and presents the marginal effects for platform failure probabilities using the following equation.

$$\Pr(Defunct_{it}) = \Phi(\alpha + \beta \times FinSOE_i + \theta \times NFinSOE_i + \gamma \times Control_{it} + Province_i + Week_t + \varepsilon_{it}).$$

FinSOE is taking a value of one for a platform if it is affiliated with an SOE running a financial business. *NFinSOE* is equal to one if the platform is only affiliated with nonfinancial SOE(s) and zero otherwise. The estimation results from Column (1) to Column (4) in two panels are based on the trading sample, with size, age, term, week fixed effects, and province fixed effects controlled. The estimation results in Column (5) in both panels are based on the long sample using the probit model, with size, age, week fixed effects, and province fixed effects controlled. *Trading Volume* is the total funding facilitated by the platform. *Number of Investors* is the number of investors on the platform. *Number of Borrowers* is the number of borrowers on the platform. *Interest Rate (%)* is the weighted annualized percentage rate of the platform loans weighted by each loan amount. *Defunct i*s equal to one for platforms ceasing to exist at time *t* and zero for surviving platforms. T-statistics are reported in parentheses. *** indicates the coefficient is different from zero at the 1% level, ** at the 5% level, and *at the 10% level.

Panel A. P2P Platform Performance and Central-SOE Affiliation

	(1) Ln(Trading Volume)	(2) Ln (#Investors)	(3) Ln (#Borrowers)	(4) Interest Rate (%)	(5) Probit (Defunct =1)
CentralSOE	1.027***	1.417***	0.713*	-2.005***	-3.541%***
	(3.644)	(3.688)	(1.801)	(-4.470)	(-54.624)
NCentralSOE	0.697***	0.629***	0.013	-2.174***	-0.693%***
	(5.293)	(2.939)	(0.077)	(-5.914)	(-8.174)
Controls, Province FE, Week FE	Y	Y	Y	Y	Y
Observations	128,673	128,673	128,673	128,673	397,617
R-squared	0.285	0.219	0.274	0.275	0.104

Panel B. P2P Platform Performance and Financial-SOE Affiliation

	(1) Ln(Trading Volume)	(2) Ln (#Investors)	(3) Ln (#Borrowers)	(4) Interest Rate (%)	(5) Probit (Defunct =1)
FinSOE	1.483***	1.353**	0.926*	-2.653***	-3.665%***
	(5.374)	(2.504)	(1.905)	(-4.777)	(-48.109)
NFinSOE	0.652***	0.721***	0.048	-2.044***	-0.710%***
	(4.978)	(3.617)	(0.285)	(-6.030)	(-8.292)
Controls, Province FE, Week FE	Y	Y	Y	Y	Y
Observations	128,673	128,673	128,673	128,673	397,617
R-squared	0.287	0.218	0.274	0.275	0.104

Appendix A. Individual Examples on Defaults and Bailouts

When a platform fails, what happens? We first examine the 16 defunct SOE-affiliated platforms in our sample. By the end of our sample, at least four of them have returned investors' investment. We find almost no complaint on each platform's discussion board. We also examine the 10 largest defunct non-SOE platforms by collecting news on the Internet. These platforms simply shut down the platform's website and disappear, leaving investors complaining on discussion board. Below we provide two examples at default risk, one is affiliated with SOE, and one isn't.

For the SOE-affiliated platform, the platform "Lian Che Jin Fu" (LCJF), is affiliated with an SOE "Guang Da Li He" (GDLH), a subsidiary of China State Construction Engineering Corporation Limited. On October 11, 2017, the platform LCJF announced on its website that because of one borrower's default, the due principal and interest cannot be paid to the investors on time. To pay back investors, the platform itself was actively collecting proceeds from the borrowers. The event led to heated discussions and complaints from investors. On the following day, October 12, 2017, the platform LCJF published a letter from the SOE GDLH. The letter stated that the SOE GDLH would bail out the platform and pay back the loan's principal and interests to investors. The SOE GDLH explained the bailout decision is to protect investors' trust in the SOE GDLH, because the investors invest in the P2P LCJF based on their trust on GDLH. On October 13, 2017, investors get their money back, according to the discussion board. We have no information on many bailouts, and we don't know whether bailout is representative.

For the non-SOE affiliated platforms, we found an example of "Ezubao". This platform was founded in 2014, and they attracted capitals from approximately 900,000 investors, in the amount of approximately 50 billion Chinese Yuan (around $7.6 billion). The platform was shut down in December 2015, because it was reported to operate as a Ponzi scheme. The platform's founders were then sued and imprisoned. However, the salvage value from the platform and the founders is far below the amount they borrowed from the investors, so most of the investors lost big in this platform.

One popular approach that many platforms take for risk control is to form internal reserve funds to cover potential defaults. The P2P platforms are not required to report any details on these reserve funds. However, from IPO filings or other filings of platforms, which went public, we are able to collect two examples. First, in the IPO filings[9] of Jiayin Group Inc., which owns a P2P platform called "Niwodai", Jiayin states that it runs an "investor assurance program" which protect investors investments. From 2016 to 2018 September, the total payouts, which are total amount of cash paid to investors upon borrower's default, amount to RMB 5.7 billion (US$0.8 billion). Second, from the SEC filing, a U.S. listed Chinese P2P lending company "PPdai Group Inc." runs a "quality assurance fund" and "investor reserve funds", with payout amounting to RMB 3.03 billion (US$ 0.44 billion) from 2015 to 2017 according to its form-1 filing.[10]

[9] https://www.nasdaq.com/markets/ipos/filing.ashx?filingid=13116225, accessed on March 14, 2019.
[10] https://www.sec.gov/Archives/edgar/data/1691445/000119312517309953/d285990df1.htm, accessed on March 14, 2019.

Appendix B. Additional Details on Regulations

Before 2015, there is no specific regulation on platforms. In July 2015, the People's Bank of China, or the PBOC, together with nine other regulatory agencies, jointly issued "The Guidelines on Promoting the Healthy Development of Internet Finance", or "The Guidelines".[11] The Guidelines seek to promote development of Internet Finance, or FinTech, encourage financial innovation, and believe that FinTech has a positive impact on both traditional financial sector and the overall economy, especially for small-and-medium-sized firms' development. One field that the Guidelines encourage is online peer-to-peer lending. Additionally, the Guidelines formally introduced for the first time the regulatory framework and basic principles governing the P2P lending industry. The Guidelines define online peer-to-peer lending as direct lending between individuals through an online platform, which is under the supervision of the Chinese Banking and Regulatory Commission (CBRC) and governed by the PRC Contract Law, the General Principles of the Civil Law of the PRC, and related judicial interpretations promulgated by the Supreme People's Court. Pursuant to the Guidelines, a company that provides online peer-to-peer lending information intermediary services shall function solely as an information intermediary and provide information services rather than provide credit enhancement services or engage in illegal fund-raising for platform itself.

After 2015, as fraud and scandals appeared more frequently in the media and began to negatively affect investors (for example, Ezubao, which collapsed in December 2015), the CBRC took actions to standardize the industry by introducing a series of detailed measures. In August 2016, the CBRC and other four regulatory agencies issued "The Interim Measures on Administration of Business Activities of Online Lending Information Intermediaries", or "The Interim Measures".[12] The Interim Measures further define P2P lending platform as online lending information intermediary and prohibit P2P platforms from engaging in certain activities, including among others, (i) fundraising for the platforms themselves, (ii) holding investors' fund, including accepting, collecting or gathering funds of lenders directly or indirectly,[13] (iii) providing guarantee to investors as to the principals and returns of the investment, (iv) raising funds by issuing financial products as wealth management products, (v) mismatch between investor's expected timing of exit and the loan's maturity date, (vi) securitization, (vii) promoting its financing products on physical premises other than through the permitted electronic channels, such as telephones, mobile phones and Internet,[14] (viii) providing loans with its own capital, except as otherwise permitted by laws and regulations, (ix) equity crowd-funding, (x) deducting interest from loan principal, (xi) outsourcing key services such as customer information collection, screening, credit evaluation, (xii) facilitating loans without a designated purpose[15], and (xiii) cheating.

Since the Interim Measures prohibit platforms from providing security or guarantee to

[11] Official site for the Guideline: http://www.gov.cn/xinwen/2015-07/18/content_2899360.htm, accessed on March 14, 2019.
[12] Official site for the Interim Measures: http://www.cbrc.gov.cn/govView_37D312933F1A4CECBC18F9A96293F450.html, accessed on March 14, 2019.
[13] This requirement leads to the introduction of the Custodian Guidelines below.
[14] This requirement aims at preventing platforms from acquiring investors offline.
[15] This requirement aims at preventing borrowers from borrowing money from P2P platform and then investing in stock market.

investors as to the principals and returns of the investment, P2P platforms increasingly replace self-managed risk reserve fund by partnering with third-party guarantors to protecting investors' interests against delinquency risks. However, the third-party protection often with an upper limit and the platforms continue to hold the rest.

To strengthen supervision on P2P lending platforms, in October, 2016, the CBRC, along with the Ministry of Industry and Information Technology and the State Administration for Industry and Commerce, issued the "Guidelines on the Filing-based Administration of the Online Lending Information Intermediaries", or "The Administration Guidelines". [16] The Administration Guidelines set out rules on the filing-based administrative regime of online lending information intermediaries that require online lending information intermediaries shall apply for value-added telecommunications business operation licenses with certificate of registration issued by the local financial regulatory authority. However, to our best of knowledge, at least until February 2019, the financial regulatory authorities are still in the process of making detailed implementation rules regarding the filing procedures and none of the online lending information intermediaries have been permitted to apply for such filing.

To prevent platforms from running away with investor' money, in February 2017, the CBRC issued "The Guidelines on Online Lending Funds Custodian Business", or "The Custodian Guidelines".[17] One of the guidelines is to require the platforms to set up custody accounts with commercial banks to keep the funds from being controlled by platforms. Through the usage of custodian banks, the proceeds of investing and collecting will go through the custodian bank, which make it less likely for platforms running away with investor's money.

To make the industry more transparent, the CBRC further issued the "Guidelines on Information Disclosure of Business Activities of Online Lending Information Intermediaries", or "The Disclosure Guidelines", in August, 2017.[18] Pursuant to the Disclosure Guidelines, P2P lending platforms shall disclose certain required information on their websites in a fair, accurate, complete and timely manner.

To the extent that the relevant P2P lending platforms are not in full compliance with the Administration Guidelines, the Custodian Guidelines, and the Disclosure Guidelines upon Guidelines' introduction, they are required to make correction or rectification within a rectification period specified by the Guidelines. As we mentioned above, until February 2019, the rectification is still in the process and none of the online lending information intermediaries have been permitted to apply for such licenses.

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[16] Official site for the Administration Guideline: http://www.cbrc.gov.cn/govView_E7B94B41E8C340E4833472632308AEC5.html, accessed on March 14, 2019.

[17] Official site for the Custodian Guideline: http://www.cbrc.gov.cn/govView_4201EF03472544038242EED1878597CB.html, accessed on March 14, 2019.

[18] Official site for the Disclosure Guideline: http://www.cbrc.gov.cn/govView_C8D68D4C980A4410B9F4E21BA593B4F2.html, accessed on March 14, 2019.

Appendix C. Robustness: sized matched pairs and data over different horizons.

This table presents the results of the ordinary least squares regression for our baseline model (1). Panel A uses sized matched pairs and Panel B uses monthly data in Panel B. This table also presents the estimates of determinants of the hazard rate to becoming a defunct platform using the Cox-proportional hazard model (2). The matched sample is constructed by matching each SOE affiliated platform with three similar-sized platforms without SOE affiliation. *Trading Volume* is the total funding facilitated in the platform. *Number of Investors* is number of investors on the platform. *Number of Borrowers* is number of borrowers on the platform. *Interest Rate (%)* is the weighted annualized percentage rate of the platform loans weighted by each loan amount, which is offered to investors. *SOE* is a dummy variable with a value of one for platforms affiliated with SOEs and zero otherwise. *Size* is measured by the registered capital of the platform. *Age* is the number of years since the platform's inception. *Term* is the weighted average term of loans from the platform weighted by each loan amount. Standard errors are clustered at both the platform and the month level. T-statistics are reported in parentheses. *** indicates the coefficient is different from zero at the 1% level, ** at the 5% level, and *at the 10% level.

Panel A. Match SOE-affiliated platforms with non-SOE-affiliated platforms by size (1:3)

	(1)	(2)	(3)	(4)	(5)	
	Ln(Trading Volume)	Ln(#Investors)	Ln(#Borrowers)	Interest Rate (%)	Cox Coefficient	Hazard ratio
SOE	0.842***	0.779***	0.259	-2.325***	-1.954***	[0.142]
	(5.479)	(3.275)	(1.260)	(-6.271)	(-7.523)	
Week FE	Y	Y	Y	Y		
Observations	35,651	35,651	35,651	35,651	520	
R-squared	0.135	0.086	0.130	0.244	0.038	

Panel B. Using Monthly Data

	(1)	(2)	(3)	(4)	(5)	
	Ln(Trading Volume)	Ln(# Investors)	Ln(#Borrowers)	Interest Rate (%)	Cox Coefficient	Hazard ratio
SOE	0.910***	0.827***	0.200	-2.360***	-2.055***	[0.128]
	(6.954)	(3.936)	(1.163)	(-7.637)	(-8.172)	
Ln(Size)	0.266***	0.367***	0.255***	-0.249***	-0.137***	
	(7.031)	(6.204)	(5.278)	(-2.765)	(-6.819)	
Ln(Age)	1.334***	1.848***	1.739***	0.816***		
	(9.993)	(9.689)	(9.047)	(2.942)		
Ln(Term)	0.955***	0.706**	2.095***	-1.935***		
	(5.310)	(2.192)	(7.002)	(-3.863)		
Province FE	Y	Y	Y	Y	Y	
Month FE	Y	Y	Y	Y		
Observations	40,908	40,908	40,908	40,908	4,210	
R-squared	0.280	0.172	0.247	0.281	0.0126	

Appendix D. The NIFA Sample and Platform Profitability

We obtain the third dataset which is collected by NIFA and we refer to it as the "NIFA sample". To standardize the P2P market, NIFA was established in March 2016 as an official self-regulatory organization of P2P platforms. Membership in NIFA is voluntary and all member platforms need to release financial reports to the public, including information on earnings, revenue, total assets, etc. There are 89 P2P platforms with NIFA membership by the year of 2016. The NIFA sample covers 40% of the existing P2P market, a fair representation of the whole market. Given that membership is promoted by the government, but not required, more SOE-affiliated platforms choose to participate compared to non-SOE-affiliated platforms.

We present summary statistics of the NIFA sample in the following table Panel A. In the first row, we compute the mean, standard deviation, and percentiles of the variable *SOE*. Given that the NIFA is established for regulation purposes, among the 89 platforms in the NIFA sample, there are 13 SOE-affiliated platforms (15.7% of the sample), suggesting that the "NIFA sample" covers more SOE platforms relative to the trading sample and long sample. In terms of other characteristics, on average, P2P platforms have registered capital of 77 million Chinese Yuan. The mean and median ages are 2.991 and 2.589 years, respectively. We find no defunct platforms in this sample. The summary statistics suggest that the "NIFA sample" covers larger and older platforms, relative to the trading sample and the long sample.

We then compare platforms profitability using this sample with the following specification:

$$Profitability_i = \alpha + \beta \times SOE_i + \gamma \times Control_i + Province_i + \varepsilon_{it}\ .$$

We measure platform profitability in three ways: *Profit_POS, ROA,* and *Earnings Ratio*. Variable *Profit_POS* is a dummy variable, taking a value of one if a platform's 2016 earnings are positive, and zero otherwise. The *ROA* is calculated as earnings over total assets and the *Earnings Ratio* is earnings over total revenue. The control variables include platform registered capital, age, and province fixed effects. Here, we do not include term as a control variable, because the data are unavailable in the NIFA sample. Additionally, given all observations are from the same date, we do not control for time fixed effects. Finally, given that this sample only contains 89 observations, we need to keep in mind that the limited number of observations might make the estimation noisy and not as precise.

We present the results in the following table Panel B. Since variable *Profit_POS* is a dummy variable, Column (1) uses probit regression, while Column (2)-(3) use OLS. In the first regression for the positive profit dummy, the coefficient on *SOE* is 0.087 but is not statistically significant. For economic meaning, the SOE-affiliated platforms are on average 3.46% more likely to have profits rather than suffer losses. For the ROA measure in the second regression, the coefficient on *SOE* is -0.161, indicating that the SOE-affiliated platforms have lower ROAs than non-SOE-affiliated platforms by 16.1% on average. For the earnings ratio in the third regression, the coefficient on *SOE* is negative at -0.254, implying that SOE-affiliated platforms on average have a lower earnings ratio than non-SOE-affiliated platforms by 25.4%. However, none of the above coefficients is statistically significant. The results suggest that there are no significant differences in the profitability of SOE-affiliated platforms and non-SOE-affiliated platforms.

Panel A. Summary Statistics (N=89)

	Mean	Std. Dev.	P1	P25	Median	P75	P99
SOE	0.157	0.366	0	0	0	0	1
Size / Registered Capital (million CNY)	76.519	55.279	10	31.579	53.125	100	200
Age (years)	2.991	1.373	0.419	2.222	2.589	3.405	7.8
Defunct	0	0	0	0	0	0	0

Panel B. Platform Profitability and SOE Affiliation

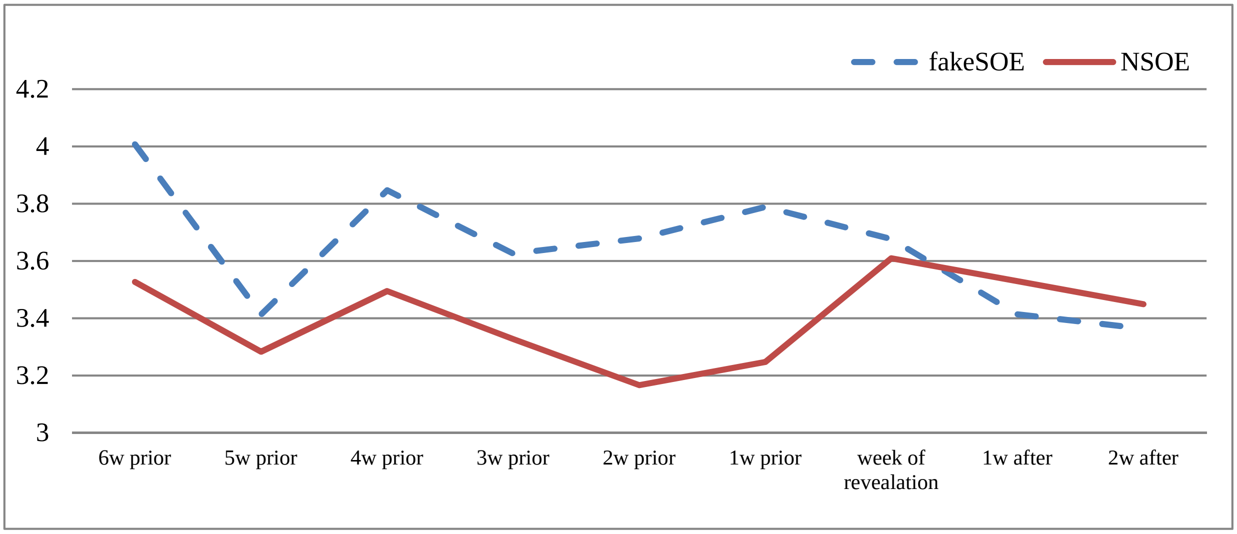
	(1)	(2)	(3)
	Profit_POS	ROA	Earnings Ratio
SOE	0.087	-0.161	-0.254
	(0.191)	(-1.511)	(-0.383)
Ln(Size)	0.366**	0.081*	0.069
	(2.007)	(1.990)	(0.268)
Ln(Age)	-0.012	0.016	-0.202
	(-0.026)	(0.153)	(-0.302)
Province FE	Y	Y	Y
Observations	89	89	89
R-squared	0.076	0.144	0.045

Note: T-statistics are reported in parentheses. *** indicates the coefficient is different from zero at the 1% level, ** at the 5% level, and *at the 10% level.

Appendix E. Additional results on fake SOE

This figure shows the performance for fake-SOE-affiliated platforms and matched non-SOE-affiliated platforms, from six weeks before the revelation of fake SOE affiliation to two weeks after the revelation. Panel A shows the results captured by the natural logarithm of trading volume and Panel B the natural logarithm of number of investors. The sample is constructed based on the matching procedure described in Section IV.A.

Panel A. Trading volume surrounding the revelation



Panel B. Number of investors surrounding the revelation