Government Affiliation and Fintech Industry:

The Peer-to-Peer Lending Platforms in China

Jinglin Jiang, Li Liao, Zhengwei Wang, and Xiaoyan Zhang*

February 2018

Abstract

Using unique hand-collected data, we examine how government affiliation influences the development of thousands of peer-to-peer (P2P) lending platforms in China. We find that P2P platforms with state-owned enterprise affiliations have higher trading volume and attract more investors. These platforms also have higher survival probabilities, especially during the 2015 Chinese stock market turbulence. We find no significant difference in profitability between P2P platforms with state-owned enterprise affiliations and those without.

Keywords: Peer-to-peer lending platforms, fintech, government affiliation, state-owned enterprise.
JEL Classifications: G21, G28, O3.

* Jiang, Liao, and Wang are from PBC School of Finance, Tsinghua University. Zhang is from Krannert School of Management, Purdue University. We would like to thank Li An, Mark Chen, Zhuo Chen, Bo Li, Bibo Liu, Zhan Shi, Hongyu Xiang, Yao Zeng, Fudong Zhang, Lu Zhang, Hao Zhou, Zhen Zhou, and seminar participants at Tsinghua University PBC School of Finance and Purdue University, for helpful comments and suggestions.

Government Affiliation and Fintech Industry:

The Peer-to-Peer Lending Platforms in China

February 2018

Abstract

Using unique hand-collected data, we examine how government affiliation influences the development of thousands of peer-to-peer (P2P) lending platforms in China. We find that P2P platforms with state-owned enterprise affiliations have higher trading volume and attract more investors. These platforms also have higher survival probabilities, especially during the 2015 Chinese stock market turbulence. We find no significant difference in profitability between P2P platforms with state-owned enterprise affiliations and those without.

Keywords: Peer-to-peer lending platforms, fintech, government affiliation, state-owned enterprise.

JEL Classifications: G21, G28, O3.

"The most appropriate government for the financial sector is not necessarily a passive one."

--Rajan and Zingales, 2004

Governments play an important role in the global financial markets. In terms of whether governments positively influence financial development, the answers vary from one country to another. On the one hand, La Porta, Lopez-de-Silanes and Shleifer (LLS hereafter, 2002) document that explicit state ownership in emerging markets is associated with lower levels of financial development; and Acharya and Rajan (2013) suggest that governments might be inefficient and myopic. On the other hand, Rajan and Zingales (2004) and Glaeser, Johnson and Shleifer (2001) suggest that governments centralize authority and are needed to create financial markets; and Acharya, Anginer, and Warburton (2016) find that governments in developed countries provide an implicit guarantee to large financial institutions, which lowers the cost of bonds for these large institutions. Given the debate on the role of government, China, the second largest economy in the world, and yet a developing country, with its government form and involvement in the market drastically differing from the western developed countries, provides a unique opportunity for us to examine the impact of government affiliation on the development of financial market. In this study, we specifically focus on the peer-to-peer lending markets, a significant component of the rising fintech industry.

Peer-to-peer (P2P) lending is the practice of lending money to individuals or businesses through online services that match lenders directly with borrowers. P2P lending, a form of crowd funding, is an important part of the fintech industry, and is an example of recent financial innovations (Shiller, 2013). Online P2P lending was first introduced in China in

2007. For the past five years, the number of P2P platforms has enjoyed annual growth rates around 60%. P2P lending has gradually become a significant source of alternative funding for small businesses and individuals in China, as well as a new and exciting investment channel for households. In the second quarter of 2017, P2P platforms facilitated 7.2% of the incremental loans extended to households and small businesses in China. From the perspective of the global fintech market, China's P2P market is twice the size of the combined value of the U.S. and the U.K. P2P markets, as documented in Liao, Wang, Xiang, and Zhang (2017). China has become a leader in the development of P2P lending platforms.

Van Horne (1985) points out that financial innovations may make the markets more efficient or more complete, and they are important for a financial system's development. However, P2P platforms, like any other financial innovation, can carry substantial uncertainties and risks. They might fail, and they might introduce greater fragility to the financial system and even lead to systemic crises, as indicated in Carter (1989) and Rajan (2006).[1] In the case of China's P2P industry, the rapid growth of P2P platforms has been accompanied by a substantial number of frauds and failures. For instance, from 2010 to 2016, over 60% of the P2P platforms ceased operation and became defunct.

Given the importance and uncertainty associated with financial innovations, what role the government should play becomes a pivotal and intriguing question. Minsky and Kaufman (2008) suggest that the government could potentially "validate the innovation, ensuring persistence of new practices". There are two approaches the government can potentially take:

[1] Beck, Chen, Lin and Song (2016) specifically discusses the bright sides and dark sides of the financial innovations using the bank industry around recent global financial crisis. They find evidence of both better growth and higher fragility associated with financial innovations, and the net is a positive net effect of financial innovation on economic growth.

hands-off monitoring or hands-on participating. In most of the developed countries, such as the U.S., the governments allow the invisible hand of the market to do its work and thus choose not to be actively involved in the operations of financial innovations. These governments focus more on monitoring and supervising, such as demanding full information disclosure (LLS, 2006), and letting the market decide the fate of financial innovations. The situation is quite different in emerging markets, such as in China. With under-developed capital markets and incomplete legal and credit system, as documented in Allen, Qian, and Qian (2005), the Chinese government chooses not to passively rely on the market power. Instead, it intends to be more actively involved in the financial innovations, and provides explicit and implicit guidance for innovations when deemed necessary. Existing research has not yet directly addressed which of these two approaches, monitoring vs. participating, is more effective or beneficial to the development of financial innovations, especially in the blooming fintech industry.

In this paper, we investigate the relation between government involvement and performance and survival dynamics of the P2P lending platforms. As suggested by DeFond, Wong, and Li (2000) and Acharya and Kulkarni (2012), we use state-owned enterprise (SOE) affiliation as a proxy for government involvement.[2] Our research questions are as follows: Does government affiliation affect P2P platform performance? Does it influence platform survival probabilities, especially during the recent stock market turbulence? In addition, do the SOE-affiliated platforms suffer efficiency losses because of the government affiliation?

[2] A strand of literature documents that SOEs could be considered as government agents in China's specific setting. For instance, 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.

Despite the importance of understanding government's role in financial innovations, such as fintech industry development, there are surprisingly few studies that consider this issue. One possible reason could be that it is quite difficult to obtain relevant and direct data on government affiliation and fintech industry, given its short history. To overcome this difficulty, we hand-collected data on thousands of P2P platforms, with substantial cross-sectional variation in government affiliations and platform performance measures. To be specific, we collect three datasets. The first dataset contains detailed weekly transaction data at the platform level for 1,500 P2P platforms from 2014 to 2017. The second dataset contains survival information for 5,000+ platforms, which covers all P2P platforms ever existed since 2010. Our last dataset contains detailed financial information for 89 platforms in 2016. These novel datasets allow us to thoroughly examine platform level performance, survival and profitability, which has been difficult for previous studies to investigate.

Our empirical results show that platforms with SOE affiliations are more likely to enjoy larger transaction volumes and attract more investors. We also find that platforms with SOE affiliations are substantially less likely to default. These results become even more prominent during the 2015 Chinese stock market turbulence, especially when the market plummets. In addition, platforms affiliated with SOEs have lower interest rates, possibly because investors are willing to sacrifice some payoffs for better performance and platform survival ability. Previous literature on SOEs has extensively documented that SOEs have lower efficiency and profitability (e.g., Sun and Tong, 2003; Song, Storesletten, and Zilibotti, 2011). We examine this hypothesis using P2P platform data, and find no significant difference in the profitability of SOE and non-SOE affiliated platforms. To summarize, government affiliation has positive impacts on P2P platforms and is associated with better performance and higher survival probability, and it does not cause significant efficiency loss.

There are several possible explanations as to why the SOE affiliation would improve the P2P platform's performance or survivability. First, it could be that the SOE affiliation provides an "implicit government guarantee".[3] In practice, P2P platforms often claim to provide principal protection for investors once borrowers default, while the creditability of the claim depends on the creditability of the platforms themselves. If a SOE affiliated platform were to face default, investors expect that the government would back up the platform and satisfy their claims. This implicit government guarantee bolsters investor confidence in SOE affiliated platforms and thus, such platforms have more investors, higher trading volumes, lower interest rates, and they survive better. Our findings are all consistent with this explanation.

Alternatively, it could also be that SOEs provide the P2P platforms better access to capitals and other business resources, so that the SOE affiliated platforms enjoy improved operational efficiencies. To investigate these possibilities, we separate platforms based on whether they are affiliated with central SOEs or local SOEs, and financial SOEs or non-financial SOEs. We find that P2P platforms affiliated with central SOEs have better performances than local SOEs. Similarly, P2P platforms affiliated with financial SOEs have better performances among SOE platforms. These findings indicate that it is possible that the

[3] As Borisova and Megginson (2011) suggest, government's presence could be viewed by investors as an assurance of repayment and protection against adverse circumstances. An implicit government guarantee helps state-owned firms to enjoy lower cost of debt (Borisova and Megginson, 2011), have better performance during the crisis (Acharya and Kulkarni, 2017), and more likely to be the beneficiaries of a government bailout (Faccio, Masulis, and McConnell, 2006). In our setting, if a P2P platform is government affiliated, investors will feel secure about getting their money back due to the implicit government guarantee (Zhu, 2016).

resources and expertise from the central and financial SOEs help to improve the operations of the P2P platforms. Notice that the above two explanations are not mutually exclusive, and they are likely both at work in reality.

Our study is related to the literature on how government involvement affects financial innovations, and the creation of a financial market. For instance, Glaeser, Johnson and Shleifer (2001) compare the government involvement on the creation of financial markets in Poland and the Czech Republic in the 1990s, and document that a highly motivated Polish government was associated with an orderly developing stock market, while a passive Czech government was associated with less orderly stock market development. Our analysis demonstrates how government affiliation affects the performance of financial intermediaries in the newly established fintech sector, suggesting that the government may shape the market in a more profound way than traditionally understood (e.g. LLS, 2006). The positive impact of government involvement to bolster fintech industry development is rarely documented in previous studies.

Our paper naturally connects to the emerging literature on P2P lending market. Most of the current P2P lending studies focus on information processing using data from a single U.S. based platform, rather than a large cross-section of platforms from another country. For instance, using data from Prosper.com, Duarte, Siegel, and Young (2012) find that borrowers with a trustworthy appearance are more likely to get funded and pay lower rates of interest. Also with Prosper.com data, Lin, Prabhala, and Viswanathan (2013) find that the online friendships of borrowers may act as signals of credit quality. Wei and Lin (2016) study the pricing mechanism of Prosper.com, and find that under platform-mandated posted prices, loans are funded with higher probability and higher interest rate than in auctions, while the default rate is also higher. Iyer, Khwaja, Luttmer, and Shue (2017) also examine Prosper.com data, and find that lenders substantially outperform credit scores in terms of predicting default due to the exploitation of nonstandard information. To the best of our knowledge, we are the first study to examine the 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.

The remainder of the article is organized as follows. In Section I, we describe the institutional backgrounds and develop our hypotheses based on previous literature. We introduce the data in Section II. Section III provides the basic empirical results on the relation between government affiliation and platform performance, survival and efficiency. We investigate other potential factors related to government affiliation in Section IV. Section V concludes.

I. Institutional Background and Testable Hypothesis

We provide a brief summary of the Chinese P2P market in Section II.A. The literature review and hypothesis are presented in Section II.B.

A. Chinese P2P Lending Market

As pointed out by Wei and Lin (2016), P2P lending is a prime example of how technological innovation has transformed the financial service industry. P2P platforms provide a marketplace where borrowers and investors engage in loan transactions. The borrowers are typically small- and medium-sized enterprises (SMEs) or individuals, whose financing needs cannot be fully satisfied by traditional financial institutions. The investors, or the lenders, are typically households and sometimes institutions.

To have an overall understanding of the importance of P2P lending market in China, we compare the key properties of P2P market in U.S. with China's P2P market. The U.S. has a well-developed financial sector, a mature credit score system and a diversity of investment choices. In the existence of large banking and investment industry, Tang (2018) finds that the U.S. P2P market serves as a supplement in the case of small size loans, and as a substitute for infra-marginal bank borrowers. Altogether, there are about 200 P2P platforms as of 2016.[4] With data from Citi Research, over the past three years, the U.S. P2P market enjoys an accumulative growth rate of 593.20%, facilitating around $45 billion loans to borrowers. In contrast, Chinese P2P platforms are much more important for investors and borrowers, and they play a much more significant role in the society. For instance, at the peak in 2015, the Chinese P2P market had over 5,000 P2P platforms. Over the past three years, the Chinese P2P market has an accumulative growth rate of 1976.29%, facilitating over $470 billion loans to borrowers. Even though the volumes and sizes of the Chinese P2P platforms are still small relative to traditional commercial banks, their prominent growth reflects the popularity and importance of this alternative funding and investing channel.

What drives the difference between the U.S. and China P2P market? In our opinion, the P2P platforms are more popular and important in China because they provide much needed services to both borrowers and investors. From the borrowers' side, the P2P market acts as an important alternative funding source for small firms and individuals. Since the credit score

[4] For more details, please see IBISWorld Industry Report OD4736 "Peer-to-Peer Lending Platforms in the US".

system in China is still in its infancy, it is quite difficult for individuals and small firms to borrow from commercial banks, due to information asymmetry and diseconomies of scale. According to Liao, Wang, Xiang, and Zhang (2017), only 21.8% of financially constrained individuals are served by the banking system, while the number for SMEs is 46.2%. The P2P market provides viable access to capital for this under-served market. When we focus on the total outstanding loans to small businesses and individuals, the proportion of loans served by the P2P market to the banking system rises from 0.4 % as of March 2015 to 2.3% as of March 2017. Even though the increase of 1.9% over 2 years might seem insignificant, considering the magnitude of the Chinese economy, that is close to half trillion dollars.

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. We present the returns on fixed income products in Figure I Panel A, using data from WIND during the 2014-2017 period. The typical annual CD rate offered by Chinese banks is 3%, and the annual return on bank wealth management products is around 5%. The P2P lending platforms on average provide investment returns over 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" investment channel, in comparison with traditional investments in fixed income, equity and real estate.

Given the substantial demand for this alternative capital channels, maybe it is not surprising that thousands of P2P platforms were founded over a short period to serve the market. With the existence of thousands of platforms in the same market, the competition for business and survival among platforms becomes crucial. Due to pressure of competition, nearly all the platforms provide implicit guarantees to investors for repayment of the loan principal (and interest in some cases) if the borrower defaults. That is, if the borrower defaults, the losses are mostly covered by the platform, which indicates that the platforms tolerate the default risk from individual borrowers.[5] As a direct result, Chinese P2P platforms preset the interest rate for investors, and they screen borrowers very carefully and require collateral from borrowers if the loan amount is relatively large. This is a unique feature of the Chinese P2P market, which is not observed in other P2P markets. Notice that the P2P platforms can default themselves. Therefore, when investors choose to invest in the P2P market, it is more important to evaluate the default risks of the platforms rather than the default risk of individual loans. The large cross-sectional variation in platforms clearly makes choosing the right platform one significant issue for all investors.

Like most of the financial innovations, the rapid growth of the P2P market has been accompanied by a large number of failures, which inevitably attracts substantial attention from regulators and the media. One famous example is a P2P platform named "Ezubao". Founded in 2014, this platform attracted capitals of about 50 billion Chinese Yuan (around

[5] The CBRC, the primary regulatory authority, tightened the regulation in August 2016 and specified that P2P platforms should operate as information intermediaries and are prohibited from engaging in illegal fund-raising and providing "credit enhancement services". Even though, the P2P platforms still provide an implicit guarantee in other forms, such as a reserve fund. For example, Renrendai.com, one of the largest P2P platform in China, introduced a risk reserve fund arrangement. Under this scheme, if a loan is delinquent for a certain period of time, Renrendai may withdraw a sum from the risk reserve fund to repay investors the principal and accrued interest for the loan in default until the risk reserve fund is depleted. See Liao, Wang, Xiang, and Zhang (2017)

$7.6 billion) from approximately 900,000 investors. The platform was shut down in December 2015, because it operated as a Ponzi scheme. In Figure I Panel B, we present the number of defunct platforms and live platforms. It is striking that at the end of 2016, out of the over 5000 P2P platforms that were founded, more than half of them ceased to exist. This triggers a debate on whether the peer-to-peer platforms can function in a sustainable way and truly benefit the society.

At the early stage of the development of P2P platforms in China, the Chinese government permitted and implicitly supported the rapid growth of the P2P industry. For instance, many P2P platforms were founded by state-owned enterprises, which indicates that the government agrees to open these P2P platforms. One potential reason is that the P2P platforms serve a population with limited access to traditional capital market, and they fit the theme of “inclusiveness” of fintech innovations as well as the government’s strategic view of “entrepreneurship and innovation by all”.[6] A couple of years later, as frauds and scandals appeared more frequently in the media and began negatively affecting small investors, the Chinese government took a series of actions to standardize the industry. In July 2015, the central government and the central bank jointly issued a regulatory framework in the form of *Guidance on Promoting Fintech’s Healthy Development* to increase the sustainability of the P2P platforms. Following the idea of the regulatory framework, the National Internet Finance Association (NIFA) was initiated in March 2016 as an official self-regulatory organization of P2P platforms, which requires the member P2P platforms to release financial reports to

---

for details.

[6] The “entrepreneurship and innovation by all”, together with “Internet Plus” action plan, was proposed in 2015 Chinese Government Work Report. Both strategies are aimed at creating a new growth engine and promoting the transformation and upgrading of China’s economy. Many of the P2P lending platforms are start-up firms, which embody the idea of entrepreneurship and promote employment.

improve the transparency of the industry.

B. Literature Review and Hypotheses Development

Given the importance of choosing the right platforms and the controversy around the P2P platforms development, it is important to understand what affects or signals the performance and continuous operation of P2P platforms. As mentioned earlier, the existence of thousands of P2P platforms present rich patterns of cross-sectional differences. Our objective is to examine whether government intervention through SOE affiliations would affect P2P platforms' performances and their survival probabilities.

Whether government intervention can boost the development of the financial service industry is an open question. One related study is Rajan and Zingales (2004), who state that a central authority is needed for creating financial markets. They argue that market transactions require a central authority to enforce them promptly at a low cost, and the government naturally enjoys a comparative advantage at acting as central authority. That is to say, at the early stage of a financial market, the government intervention can be useful for establishing the market as a central authority. In addition, the government intervention can be especially important during financial crisis. Acharya and Kulkarni (2017) examine the Indian banking system during the 2007-2009 global crisis, and find that public banks had a higher deposit and credit growth than private banks. Public banks experienced a gain of confidence as investors believed that their downside risk is minimized because of the implicit sovereign guarantee. Acharya and Kulkarni (2017) further point out that, stronger government guarantees facilitate the state-owned banks in obtaining access to cheap credit, and thus state-owned banks in India outperform private sector banks during the crisis.

In the setting of China, Boyreau-Debray and Wei (2005) examine the Chinese financial system and show that SOEs are more likely to get external financing from banks. This finding is also documented by Lu, Thangavelu and Hu (2005) and Song, Storesletten and Zilibotti (2011). Apart from easy credit, SOEs usually enjoy soft-budget constraints that help protect their business (Kornai, 1996), which may further ensure the stability of the affiliated financial firms and alleviate the concerns of individual investors who lend money to anonymous borrowers via virtual channels. As suggested by DeFond, Wong, and Li (2000) and Acharya and Kulkarni (2012), in this article we use the SOE affiliation as a proxy for government involvement or affiliation.

Our first hypothesis assigns a critical role to government affiliation in shaping financial innovation, such as the fintech industry, because general trust in new markets cannot be easily built up without a central authority, as suggested in Rajan and Zingales (2004). Thus, SOE affiliated platforms may attract more investors and enjoy better performance. Our first hypothesis is:

H1: P2P platforms affiliated with SOEs are more likely to be trustworthy than platforms that are not, and thus attract more investors and trading volumes.

When P2P platforms face unfavorable conditions, for example, massive borrower defaults, government affiliation might provide these platforms with cheap credit access, and reduce the platform default risk. That is, SOE affiliated P2P platforms are more likely to survive, especially during market down time. Our second hypothesis becomes:

H2: SOE affiliated P2P platforms are more likely to survive.

With the business model of principal guarantee, the P2P platforms, rather than the lenders, tolerate the default risks from borrowers. If the platform provides downside protection, investors are less likely to suffer an unexpected loss. In this case, the investors would agree to lower rates of return when investing in platforms with government affiliations, which leads to our third hypothesis:

H3: P2P platforms with SOE affiliation are more likely to have lower interest rates, because their investors might be willing to sacrifice some return for the higher survival probability of these platforms.

A large strand of literature, such as Megginson, Nash, and Randenborgh (1994) and Dewenter and Malatesta (2001), has shown that government ownership is less efficient than private ownership. According to Bai, et al. (2000), and Bai, Lu, Tao (2006), SOEs may have poor financial performance, because other than profitability, they also need to meet many social objectives, such as promoting employment and financing strategic but unprofitable projects. Similar arguments can be applied to P2P platforms with SOE affiliations, and therefore our fourth hypothesis is:

H4: P2P platforms with SOE affiliations are more likely to have lower efficiency and lower profitability.

II. Data

In Section II.A, we describe our datasets and define key variables. We present summary statistics in Section II.B.

A. Datasets

Most existing studies on P2P lending use data from the U.S., and they typically only examine one platform, for instance, Prosper.com (Duarte, Siegel, and Young, 2012; Wei and Lin, 2016). The data on P2P platforms is challenging to collect, because no regulation requires them to periodically update their data or make the data public. Most of the previous U.S. studies use Prosper.com data because the company voluntarily makes their data available to the public. In our case, we are fortunate to have obtained data for thousands of platforms in China.

We use three sets of data in this study. The first dataset contains weekly trading data for various P2P platforms, and we hereafter refer to this sample as the "trading sample". The data is collected from a website called "Home to P2P platforms", www.wdzj.com, the largest online information provider for P2P platforms in China founded in 2011. Specializing in P2P market studies, www.wdzj.com is the most popular information platform in the Chinese P2P market. It collected weekly trading data on 1,694 P2P platforms between January 1, 2014 and July 15, 2017 (the most recent week available as of the start of this study). The trading information includes trading volume, interest rate, term (time to maturity), number of borrowers and investors for each platform.

We apply the following filters to the raw data. First, to get rid of the tiny platforms, we require each platform to have at least 5 million Chinese Yuan in registration capital to be included in this sample. This filter eliminates 5% of the sample with the remaining sample containing 1,593 platforms with about 107,000 platform-week observations. Second, to mitigate the backfill bias, we exclude data from the first 26 weeks for each platform. Third, to eliminate reporting errors and outliers, we winsorize trading volume, number of investors, number of borrowers, interest rate, and registration capital at the 1^{st} and 99^{th} percentiles. The remaining 1,593 platforms in the sample contain 1,371 live platforms and 222 defunct platforms.

In terms of the trading data, the www.wdzj.com is a self-reported database, and P2P platforms might choose to join the database of www.wdzj.com (free of charge) and provide trading data because it is one important way to market their products. Therefore, self-selection becomes a potential concern. To examine the representativeness of the dataset, we compare the trading volume of the whole P2P lending market in July 2017, with the platforms in the trading sample. The P2P platforms in our trading sample cover 80% of the total number of platforms and 90% of the total transaction volume in the Chinese P2P market. Accordingly, we believe our sample fairly represents the P2P platform universe.

Our second dataset contains the basic information of across thousands of P2P platforms in the Chinese P2P lending markets, and we refer to this sample as the “full sample”. As mentioned earlier, from 2011 to 2016, more than 5000 platforms came into existence in this market, and over 3000 platforms ended in failure. Before this study, no existing database aggregated the information on the life cycles of these platforms. In order to establish this unique database, we hired 10 Ph.D. students from Tsinghua University to hand collect the information. Given the wide coverage of www.wdzj.com on all P2P platforms, we first collect the platforms’ name from www.wdzj.com, and then hand-collect the basic information from the platforms’ homepages and National Enterprises Credit Information Publicity System. For detailed information of defunct platforms, we cross check their historical information via web.archive.org, a U.S.-based website taking snapshots of all public websites automatically. The data items collected include platform name, inception date, amount of capital at time of registration, holding structure, and defunct date (if applicable). We are able to obtain information for 5,498 platforms, which covers nearly all of the P2P platforms that have existed since 2010. To exclude tiny platforms, we require each platform to have at least 5 million Chinese Yuan registered capital to be included in this sample. This filter leaves a sample of 4,208 platforms.

The third and last dataset is collected by NIFA, and we refer to it as the "NIFA sample". In an effort 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, revenues, total assets etc. As of September 2017, NIFA membership consists of 89 P2P platforms. The NIFA sample covers 40% of the existing P2P market, a fair representation of the whole market. Given the membership is promoted by the government but not required, more SOE affiliated platforms choose to participate compared to non-SOE affiliated platforms.

B. Summary Statistics on Key Variables

Affiliation with the government is an important feature that P2P platforms advertise prominently on their websites to attract investors. As mentioned earlier, we use the SOE affiliation as a proxy for government involvement. To obtain this information, we manually check a platform's shareholders in the National Enterprises Credit Information Publicity System. A P2P platform is identified as a SOE affiliated platform if the government, central or local, is among its ultimate shareholders; otherwise, it is identified as a non-SOE affiliated platform. Typically, a SOE-affiliated platform is founded jointly by a subsidiary of a state-owned enterprise and other private entities. The dummy variable, *SOE*, takes the value of one when a P2P platform is identified as a SOE affiliated platform, and zero otherwise.

[Place Table I around here]

We present summary statistics of the trading sample in Table I Panel A. In the first row, we compute the mean, standard deviation and percentiles of the variable *SOE*. We find that 8.6% of the observations are from platforms with SOE affiliations. Next, we present summary statistics on platform performance measures. The first variable is *Trading Volume,* defined as the weekly total of loan funding. The mean and median values for trading volume are 27 and 4 million Chinese Yuan, respectively. Thus, P2P platforms are relatively small compared to the traditional loan providers, such as commercial banks. For *Number of investors*, the mean and median are 1,131 and 97 each week. The mean and median for *Numbers of borrowers* are 225 and 4, respectively. With means significantly higher than the medians, all three above variables display positive skewness, in the pooled trading sample. Therefore, in later empirical testing, we use the natural logarithm of these variables. The *Interest Rate* is computed as a weighted average of the annualized percentage return rate of the facilitated loans during the week at the platform level, weighted by each loan's amount.[7] The mean and median interest rates are 12.9% and 12.1%, respectively. As we describe in Section II.A, the P2P lending rate is much higher than those offered by bank deposits and wealth management products.

We also provide basic information for platforms. The mean and median registration capitals of the platforms are 54 and 30 million Chinese Yuan, respectively. We later use the

[7] It is usually preset by the platforms according to borrower's risk profile. We perceive it as an equilibrium rate which meets both investors' and borrowers' supply and demand.

registration 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 1.853 and 1.679 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 0.369 and 0.251 years, or namely, around 4.4 and 3 months, respectively. This implies that Chinese P2P platforms are characterized by relatively short-term loans. In later regression analyses, we also take the log of the above variables in case the variables exhibit a non-normal distribution.[8]

Table I Panel B reports the summary statistics of the full sample. The SOE variable has a mean of 0.031, a median of zero, which indicates that there are 3.1% of the total platforms with a SOE affiliation. In terms of other platform characteristics, on average, P2P platforms have registration capital of 43.51 million Chinese Yuan. The mean and median for age is 1.338 and 1.262 years, respectively. We compute variable *defunct* as a dummy variable, taking a value of one when the platform ceases to exist as of November 30, 2016, the ending date of data collection, and zero for surviving platforms. We find that 62.7% of the total P2P platforms have become defunct as of November 2016. This implies that P2P lending

[8] In the Internet Appendix, we compare the features for platforms affiliated with SOEs versus those not in the trading sample. Table A2 Panel A shows that platforms affiliated with SOEs have higher average trading volume and number of investors (both significant at the 1% level). Notably, SOE platforms show a lower number of borrowers than their non-SOE counterparts at the 5% level. SOE platforms' average interest rate is almost three points (nearly one-third a standard deviation) below the average for non-SOE platforms. Panel A also shows that, for all variables used to construct the regression controls, SOE platforms' average values differ from those of non-SOE platforms. SOE platforms, with average size/registration capital of 62.78 million CNY, have about 20% more registration capital than non-SOE platforms' with 53.23 million CNY on average; survive and operate for a longer time; and have a greater tendency to facilitate longer term loans.

platforms are highly risky, which emphasizes the importance of choosing right platforms.[9] To understand how the trading sample platforms in Panel A differ from full sample platforms in Panel B, we take a snapshot in November 2016 for both the trading sample, which contains 1,586 platforms, and the full sample, which contains 4,208 platforms. We find that the trading sample contains more SOE-affiliated platforms, less defunct platforms, and they survive for a longer time than platforms in the full sample.

We present summary statistics of the NIFA sample in Table I Panel C. In the first row, we compute the mean, standard deviation and percentiles of the variable *SOE*. Given the NIFA sample is constructed under regulation, among the 89 platforms in the sample, there are 13 SOE platforms, 15.7% of the observations, suggesting that the "NIFA sample" covers more SOE platforms relative to the trading sample and full sample. In terms of other characteristics, on average, P2P platforms have registration capital of 76.519 million Chinese Yuan. The mean and median for age is 1.991 and 2.589 years, respectively. We find no defunct platforms in this sample. The summary statistics suggest that "NIFA sample" covers larger and older platforms, relative to the trading sample and full sample.

III. Main Results

In this section, we examine how SOE affiliation affects P2P platform performance. We start with a baseline regression using the trading sample in Section III.A. In section III.B, we link a platform's affiliation to its survival using the full sample. We take a close look at the

[9] We compare the features for platforms affiliated with SOEs versus those not in the full sample. Table A.2 Panel B shows that platforms affiliated with SOEs have larger in size, live for a longer time, and are more than seven times less likely to fail. Table A.3 lists the defunct reasons for the 2,639 defunct platforms in the full sample, with close to 40% of platforms being fraudulent platforms, 18% of platforms liquidate due to bad performance, and the rest defunct for unknown reasons.

stock market turbulence in Section III.C. Finally, we examine the efficiency of P2P platforms by investigating their profitability measures in the NIFA sample.

A. SOE Affiliation and Performance

To test Hypothesis I on how SOE affiliation affects platform performance, we estimate the following model for platform *i* at week *t*:

$$Performance_{it} = \alpha + \beta \times SOE_i + \gamma \times Control_{it} + \zeta_t + \varepsilon_{it}. \tag{1}$$

For a typical P2P platform, the main source of its revenues is the origination fees, charged to borrowers for facilitating the funding of loans, plus the servicing fees to investors for processing and passing proceeds.[10] Therefore, we measure $Performance$ by *Trading Volume*, *Number of Investors,* and *Number of Borrowers*, because they are all positively related to the platform revenues.

Following literature on hedge funds, such as Ackermann, McEnally and Ravenscraft (1999), we include the following three control variables: platform size, age, and the term of loans. We use the platform's registration capital as a proxy for *Size*.[11] 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 platform *i* during week *t*. Variable ζ_t represents a time fixed effect and we use week dummies. The time fixed effect controls for all aggregate effects, including seasonality, the business cycle, and trends in P2P lending over time. We double cluster standard errors at both the platform level and week level, because the performance for a given platform may be correlated over

[10] According to Lending Club corporation's 2013-16 annual reports, over 80% of the total revenue comes from the origination fee.
[11] The registration capital is not a perfect proxy for size, because it stays constant over the life of the platform. Due to data limitations, we don't have better data on platform size.

time and the performances across the platforms for a given time may be correlated as well.

[Place Table II around here]

Table II reports the regression results on how SOE affiliation affects our 3 performance measures. In the first regression for trading volume, the coefficient on SOE is 0.706 with a t-statistic of 5.280. That is to say, a SOE affiliated platform on average has 102.59% ($= \mathrm{e}^{0.706} - 1$) more trading volume than a non-SOE platform. In the second regression for number of investors, the coefficient on SOE is 0.617, with a significant t-statistic of 3.006. Economically, a SOE affiliated platform attracts 85.34% ($= \mathrm{e}^{0.617} - 1$) more investors than a non-SOE platform does on average. For the third regression on number of borrowers, the coefficient on SOE is 0.067, with an insignificant t-statistic of 0.390. In terms of magnitude, a SOE platform has 6.93% ($= \mathrm{e}^{0.067} - 1$) more borrowers than a non-SOE platform.

Maybe it is 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 is a useful signal that investors can use to choose the right platform, and that is why it is important for explaining the number of investors. For borrowers, because of the payback guarantee from the platforms, the platforms tolerate most of the credit risks from the borrowers, which make the platforms very 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.

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, the longer terms of loans tend to attract more traffic. The R^2s for all three regressions are around 20%.

Our findings in Table II largely support Hypothesis 1. That is, platforms with SOE affiliations are more likely to attract higher trading volumes, more investors and more borrowers.

B. SOE Affiliation and Survivals

Our second hypothesis is that SOE affiliated platforms are more likely to survive. Because the full sample has comprehensive coverage of all P2P platforms, we use the full sample to test this hypothesis.

The dependent variable is $Defunct_{it}$ which is a dummy variable, taking a value of one for a platform *i* at week *t* if the platform is defunct during week *t*, and 0 otherwise. We manually check the reason why each platform ceased operation in the dataset, and report summary statistics in the Appendix Table A3. We find 40% of the defunct platforms closed due to frauds, 18% closed due to operational or performance failures, and we couldn't identify exact reasons for the rest 42% of the defunct platforms.

Using the full sample, we estimate the platform default probability with a probit model for platform *i* at week *t*,

$$\Pr(Defunct_{it}) = \Phi(\beta * SOE_{it} + \gamma Control_{it}), \quad (2)$$

where we include registration capital and age as control variables. We don't control for term because the data is not available for all firms in the full sample. This model is estimated over 4,208 platforms on a weekly basis.

Estimation results for the probit regression are presented in the left panel of the Table III. The coefficient on the SOE variable is -0.777 with a significant t-statistic of -8.947. The negative sign shows that SOE affiliated platforms have lower default probability. In economic terms, the marginal effect, computed at the average value of the other right-hand side variables, indicates that the P2P platforms affiliated with SOEs have a weekly failure rate that is 1.732% (or 90.064% over one year) less than that of non-affiliated P2P platforms. This finding is consistent with hypothesis II that SOE affiliated platforms have higher survival probabilities. The coefficients on the control variables are significant with larger platforms and older platforms surviving better.

[Place Table III around here]

In addition to the probit estimation, which is more about unconditional probability, we also estimate hazard functions following Cox (1972), which is more about conditional probability, as further verification of our result. Notice that at each data collection, the surviving P2P platforms' survival variable are right-censored. In this situation, Kiefer (1988) points out that the Cox analysis can fit better than the probit model when we analyze the duration of the subjects and account formally for the right-censoring of the data. Accordingly, Lunde, Timmermann, and Blake (1999) and Brown, Goetzmann, and Park (2001) use this method to test for mutual funds and hedge funds survivals. Suggested by Seru, Shumway, and Stoffman (2009), we estimate the following Cox model at the end of November 2016:

$$h_i(t) = h_0(t)\exp(\delta_1 SOE_i + Control_i'\delta), \tag{3}$$

where the hazard rate, $h_i(t)$, is platform *i*'s probability of failing at time *t* conditional on not failing until time *t*, and $h_0(t)$ is the baseline hazard function. The coefficient on SOE

reflects the change in the hazard rate when the platform is affiliated with an SOE. A negative estimate of δ_1 implies that SOE platforms are less likely to fail than a non-SOE platform. Platform size is included as a control variable. We exclude platform age because the Cox analysis has already accounted for the duration the platform has been in existence when estimating δ_1.

We report the Cox analysis results in the right half panel of Table III. The coefficient on the SOE variable is -2.413, with a significant t-statistic of -7.980 with standard errors clustered by platform as in Heimer (2016). The negative sign indicates that SOE affiliation significantly reduces the conditional default probability. In economic terms, the hazard ratio is 0.09, meaning that the conditional failure probability for P2P platforms with SOE affiliation is 9% of that for P2P platforms without SOE affiliation.

Our second hypothesis that P2P platforms with SOE affiliation are more likely to survive is therefore supported by the empirical results. In terms of the underlying mechanism, one possible reason is that SOE affiliated platforms are more likely to have implicit government guarantee, or maybe they have access to cheaper capital, than non-SOE affiliated platforms.

C. Recent Chinese Stock Market Turbulence

The Chinese stock market experienced a phenomenal roller-coaster ride over the past couple of years. Between September 2014 and March 2015, the Chinese stock market first experienced a steep increase in growth, and the Shanghai Stock Exchange Composite Index (SSECI) surged by nearly 60%. The two months after April 2015 witnessed the SSECI rise almost another 40% and reaching its peak on June 12, 2015. 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. Between October 2015 and end of our sample in July 2017, the market slowly recovered.

The large market oscillations bring tremendous uncertainty and instability to both the financial markets as well as the society at large. Large volatilities also bring challenges to the relatively young P2P platforms. The recent stock market turbulence in China provides a unique opportunity to examine the relation between government affiliation and P2P platform performance, especially when the market falls. On the one hand, investors might avoid a volatile stock market, and find alternative investment channels, such as P2P platforms (especially those with higher creditability), more attractive. On the other hand, the massive volatility in the stock market might generate widespread panic, and investors may also run away from the P2P market to safer havens, such as deposits at banks or other financial institutions.

In case P2P platform dynamics differ during market upturns and downturns, we separate the recent market turbulence into a *rising* period, from September 2014 to April 12, 2015, and a *falling* period, April 13, 2015 to June, 2016. We then connect P2P platform performance to SOE affiliation for the two separate periods using equation (1).

Table IV reports the performance estimation results, with the left panel representing the results from the rising sub-period, and the right panel representing the results from the falling sub-period. In each panel, we present results on trading volume, number of investors and number of borrowers. As before, we control for platform size, age, term, and macroeconomic trends using week fixed effects. Standard errors are double clustered by platform and week.

[Place Table IV around here]

During the rising period, for trading volume, the coefficient on SOE is 0.401, with a significant t-statistic of 2.123. This implies that SOE affiliation improves platform trading volume significantly. We also observe a positive association between SOE and number of investors with a coefficient of 0.493, with marginal significance. There is no significant connection between SOE and number of borrowers. So when the stock market rises, the SOE affiliation in general helps platform traffic, but with varying significance.

When the market is falling, as shown in the right panel of Table IV, the magnitude and significance of the SOE coefficients are larger. For instance, for trading volume, the SOE coefficient is 0.685 (t-statistic = 4.573), which is larger than the 0.401 coefficient for the rising period. In the case of number of investors, the coefficient of 0.495 for the falling period is about the same as 0.493 for the rising period, but with a much more significant t-statistic of 2.082. For number of borrowers, the SOE coefficient is not significantly different from zero.

Therefore, irrespective of the market rising or falling, platforms affiliated with SOEs are more likely to have larger trading volumes and more investors. The results imply that government affiliation plays a role in both cases, and the results in Section III.A are not driven by only one sub-period. Meanwhile, the coefficients in the falling period are generally larger and more significant than those in the rising period. It is possible that during a stock market downturn, the massive volatility in the stock market trigger investors to put more weight on credit profiles when choosing alternative investment channels. Government affiliation, in this case, signals a better credit profile with a lower default probability, and thus attracts more trading volume and investors.

Next, we explicitly investigate the default probability during this period. We conduct a survival analysis, as in Section III.B., on a subsample of the Chinese stock market turmoil over April 2015 to June 2016. In this subsample analysis, we require the platforms to be founded before January 1, 2015. The subsample contains 1,754 platforms, of which 77 are SOE affiliated.

[Place Table V around here]

Table V shows the summary statistics of the subsample. In terms of survival as of June 2016, 773 platforms, or equivalently 44.1% of the platforms in the subsample, cease to exist. *None* of the 773 defunct platforms is affiliated with an SOE. This distinctive pattern provides strong evidence that SOE affiliated platforms are much less likely to default than non-SOE platforms during the market turmoil. In terms of why, with no direct data on a platform's capital access, it is hard to test. But it is conceivable that the government might provide an implicit guarantee or cheaper capital access in an unforgiving business environment.

To summarize, Hypothesis I and II are both supported during the turbulence period. The P2P platforms affiliated with SOEs tend to have better performances and higher survival probabilities, than those without SOE affiliations, especially during the market downturn.

D. SOE Affiliation, Interest Rates and Efficiency

According to our third hypothesis, because SOE affiliated platforms have higher survival probabilities, investors would accept lower rates of interest offered by SOE affiliated platforms. We use the trading sample to test this hypothesis, by estimating the following specification for platform *i* at week *t*:

$$InterestRate_{it} = \alpha + \beta \times SOE_i + \gamma \times Control_{it} + \zeta_t + \varepsilon_{it} \,. \tag{4}$$

Table VI provides the results. The coefficient on SOE is -2.220 with a t-statistics of -6.691, suggesting that the interest rates offered by a SOE affiliated platform are 2.220% lower than a non-SOE affiliated platform. The result clearly supports Hypothesis 3. With the principal payback guarantee, the P2P platforms tolerate most of the default risks from borrowers. So the interest rate is generally preset for investors by the P2P platforms. Government affiliation signals higher creditability, and thus investors are more willing to invest in such platforms. In this case, they accept a lower rate of return when investing in platforms with a government affiliation.

[Place Table VI around here]

Our finding that SOE platforms offer lower interest rates to investors is very similar with Allen, Gu, Qian, and Qian (2017) and Acharya, Anginer, Warburton (2016). Allen, Gu, Qian, and Qian (2017) examine Chinese trust products, and they 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 guarantee affects the pricing. Acharya, Anginer, Warburton (2016) examine the relation between the risk profiles of U.S. financial institutions and the credit spreads on their unsecured bonds, and find that the risk-to-spread relation is significantly weaker for the largest institutions, who enjoy the implicit “too-big-to-fail” guarantee from the government.

One direct consequence of lower interest rates for SOE affiliated platforms is that these platforms may be able to keep more cash flow for themselves, assuming the loan qualities are similar among SOE affiliated platforms and non-SOE affiliated platforms. This could mean that the SOE affiliated platforms have better profitability. Previous literature, such as Dewenter and Malatesta (2001), and Sun and Tong (2003) actually argue that SOEs themselves are inefficient and are not as profitable as private firms, because they, the SOEs, need to fulfill other social objectives beyond just profitability. Following the previous literature, our fourth hypothesis then predicts that SOE-affiliated platforms might be less efficient and have lower profitability.

As an emerging market place, P2P platforms are not required to report their financial statements to the public. Luckily, with the establishment of NIFA, financial data for 89 member P2P platforms is available to the public. We test our fourth hypothesis with the following specification,

$$Profitability_{it} = \alpha + \beta \times SOE_i + \gamma Control_{it} + \varepsilon_{it} \, . \tag{5}$$

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 registration capital and age. Notice that this sample only contains 89 observations. One concern is that the limited number of observations might make the estimation noisy and not as precise.

[Place Table VII around here]

We present the results in Table VII. In the first regression for the positive profit dummy, the coefficient on SOE is 0.347, but not statistically significant. That is to say, the SOE-affiliated platforms are 34.7% more likely to have a positive coefficient, but it is not significant. For the ROA measure in the second regression, the coefficient on SOE is -0.078, indicating the SOE-affiliated platforms have lower ROAs than non-SOE affiliated platforms by 7.8%. For the earnings ratio in the third regression, the coefficient on SOE is positive at 0.017, implying that SOE platforms have a higher earnings ratio than non-SOE platforms by 1.7%. None of the coefficients is significant. The results in Table VII suggest that there are no significant differences in the profitability of SOE affiliated platforms and non-SOE affiliated platforms, which is inconsistent with the efficiency loss hypothesis.

IV. Further Discussion and Channels

In this section, we consider other variables that could potentially affect the impact of government affiliation on a P2P platform's performance, which could shed some light on the underlying channels and mechanisms of the impact. In Section IV.A, we separate the SOEs into the central SOEs and the local SOEs. In Section IV.B, we compare financial SOEs and non-financial SOE. We discuss potential channels in section IV.C.

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. This is directly linked to the implicit guarantee hypothesis. If that is the case, P2P platforms affiliated with central SOEs are more likely to perform better relative to platforms not affiliated with central SOEs.

To examine the difference between the impact of central SOEs and non-central SOEs, we estimate the following specification:

$$Performance_{it} = \alpha + \beta * CentralSOE_i + \theta * NCentralSOE_i + \gamma Control_{it} + \zeta_t + \varepsilon_{it} , \qquad (6)$$

where *CentralSOE* is a dummy variable which equals one, if the State Council (central government) is one of the ultimate shareholders of the P2P platform, and zero otherwise. Variable *NCentralSOE* is also a dummy variable, taking a value of one if the platform is only affiliated with non-central SOE(s), and zero otherwise. Among the 114 SOE-affiliated platforms in the trading sample, 31 (or equivalently 27.19%) platforms are affiliated with central SOE(s).

[Place Table VIII around here]

The regression estimates are presented in Table VIII Panel A. We consider the impact on trading volume, number of investors, number of borrowers, and interest rate in four regressions. For trading volume, the coefficient on *CentralSOE* is 1.069 with a t-statistic of 3.779, and the coefficient on *NCentralSOE* is 0.586, with a t-statistic of 4.106. As expected, the *CentralSOE* coefficient is larger than the *NCentralSOE* coefficient, consistent with the implicit guarantee hypothesis. In economic terms, a platform affiliated with a central SOE averages 191.25% $(= e^{1.069} - 1)$ more trading volume compared to a non-SOE affiliated platform, while the number for a platform with a non-central SOE is 79.68% $(= e^{0.586} - 1)$. From unreported results, the difference between these two coefficients is significantly different from zero.

Results in the next three regressions are quite similar. In terms of number of investors, the coefficients on *CentralSOE* and *NCentralSOE* are 1.171 and 0.434, respectively, and both are statistically significant. Again, central SOE affiliated platforms attracts more investors than non-central-SOE affiliated platforms, and both do better than non-SOE affiliated platforms. The results on number of borrowers share similar pattern but are less significant. In the last regression on interest rates, the reduction from non-SOE affiliated platforms is 2.645% for central SOE-affiliated platforms, and 2.118% for non-central SOE affiliated platforms.

In general, P2P platforms affiliated with central SOEs have higher trading volume, more investors and lower interest rate than those affiliated with local SOEs.

B. Financial vs. Non-Financial SOEs

We also expect that P2P platforms affiliated with financial institutions are more likely to perform better, because presumably financial institutions have more relevant expertise, more connections in their business network, and more financing capacity compared to non-financial institutions. Our perspective is that it is possible that SOE affiliated platforms do better because they operate better than the non-SOE affiliated platforms. This is slightly different from the implicit guarantee hypothesis mentioned earlier, but the two perspectives are not mutually exclusive.

A platform is identified with a financial-SOE affiliation when there exists at least one financial institution, such as an insurance company, a mutual fund company, or an asset management company (AMC), among its ultimate shareholders. To examine the difference between the impacts of financial SOEs and non-financial SOEs, we estimate the following specification:

$$Performance_{it} = \alpha + \beta * FinSOE_i + \theta * NFinSOE_i + \gamma Control_{it} + \zeta_t + \varepsilon_{it}\ , \qquad (7)$$

where *FinSOE* is a dummy variable taking a value of one for a platform if it is affiliated with a SOE and at least one financial institution is among the ultimate shareholders, and zero otherwise. Variable *NFinSOE* is equal to one if the platform is affiliated with a SOE but has no financial institution among its ultimate shareholders and zero otherwise. Among the total 114 SOE platforms in the trading sample, there are 21 (or equivalently 18.42%) with a financial institution affiliation.

We present the regression results in Panel B of Table VIII. The pattern is quite similar to those in Panel A of Table VIII, when we compare central SOEs and local SOEs. The coefficients on *FinSOE* and *NFinSOE* for trading volume, number of investors, number of borrowers and interest rates all carry the expected signs and are all statistically significant. Interestingly, the magnitudes of the coefficients are always larger for FinSOE than for NFinSOE. For instance, for the trading volume, the coefficient on FinSOE is 1.654, and on NFinSOE is 0.517. Economically speaking, the magnitude is 422.78% ($= e^{1.654} - 1$) and 67.70% ($= e^{0.517} - 1$) more trading volume compared to platforms without a SOE affiliation. When we compare whether the difference between the financial and non-financial SOE coefficients is significant, we find that they are in most cases. The results suggest that P2P platforms affiliated with financial SOEs have higher trading volume, more investors and lower rates of interest.

C. Potential Channels

In previous sections, we provide empirical evidence that government affiliated P2P platforms have higher trading volumes and higher survival probabilities. How would government involvement affect P2P platforms performances and survivals? It is important to understand the underlying channels or mechanisms.

As mentioned earlier, one potential mechanism at work is the implicit government guarantee. Our finding that SOE-affiliated platforms are less likely to fail is consistent with this hypothesis. Given the fact that most of the Chinese P2P platforms provide guarantees for investors, whether the platform guarantee really is credible is a big concern. If the platform is affiliated with SOEs, investors believe the government would step in if the platform approaches default. In other words, P2P investors expect the government to bail out the SOE affiliated platforms in the event the platform is unable to meet its obligations.

Another potential mechanism is that SOEs provide relevant expertise for the P2P platforms in operating a loan business. Our finding that platforms affiliated with financial institutions have better performance among SOE platforms is consistent with this mechanism. P2P lending is essentially a loan business, and in China's market the P2P platforms bear the credit risk of borrowers. Platforms with financial SOE affiliations are probably endowed with more expertise, a better network and more access to the capital market.

Both above mechanisms are supported by the empirical evidence, and it is likely that they are both at work.

V. Conclusion

For the past few years, P2P platforms thrive in China and provide an alternative yet important funding/investment channel, which potentially raises the welfare of both borrowers and lenders. Unlike the P2P platforms in other countries, the China P2P platforms have many different and interesting features, such as government involvement, guarantee on principals and large number of competing P2P platforms.

In this paper, we examine how government affiliation influences P2P lending platforms in China. Using unique, hand-collected platform-level data over the period from 2010 to 2017, 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 affiliation have higher survivability, and this effect is more prominent during the 2015-2016 Chinese stock market downturn. Third, there is no significant difference in the profitability between SOE-affiliated platforms and non-SOE affiliated platforms. Finally, P2P platforms affiliated with central SOEs and financial SOEs have higher trading volume, attract more investors and facilitate loans at lower interest rates than platforms affiliated with local SOEs or non-financial SOEs.

This study has several implications for investors and regulators. For example, investors can better choose among P2P platforms using SOE affiliation as a signal. For regulators, we provide evidence that government intervention might help the emerging fintech industry to develop and mature, at least at its early stage. However, it still remains an open question what would be the optimal form of government involvement, when the fintech industry gradually matures.

Reference

Acharya, V. V., D. Anginer, A. J. Warburton, 2016, The End of Market Discipline? Investor Expectations of Implicit Government Guarantees, Working Paper, NYU Stern.

Acharya, V. V., N. Kulkarni, 2012, What saved the Indian banking system: state ownership or state guarantees? *The World Economy* 35, 19-31.

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.

Acharya, V. V., R. G. Rajan, 2013, Sovereign debt, government myopia, and the financial sector, *The Review of Financial Studies* 26, 1526-1560.

Ackermann, C., R. McEnally, D. Ravenscraft, The performance of hedge funds: risk, return, and incentives, *Journal of Finance* 54, 833-874.

Allen, F., J. Qian, M. Qian, 2005, Law, finance, and economic growth in China, *Journal of Financial Economics* 77, 57-116.

Bai, C., D. D. Li, Z. Tao, Y. Wang, 2000, A multitask theory of state enterprise reform, *Journal of Comparative Economics* 28, 716-738.

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.

Beck, T., T. Chen, C. Lin, F. M. Song, 2016, Financial innovation: the bright and the dark sides, *Journal of Banking and Finance* 72, 28-51.

Borisova, G., W. L. Megginson, 2011, Does government ownership affect the cost of debt? evidence from privatization, *Review of Financial Studies* 24, 2693-2737.

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, S. J., W. N. Goetzmann, J. Park, 2001, Careers and Survival: Competition and Risk in the Hedge Fund and CTA Industry, *Journal of Finance* 56, 1869-1886.

Carter, M., 1989, Financial innovation and financial fragility, *Journal of Economic Issues* 23, 779-793.

Chen, Y., S. Démurger, M. Fournier, 2005, Earnings differentials and ownership structure in Chinese enterprises, *Economic Development and cultural change* 53, 933-958.

Cox, D. R., 1972, Regression Models and Life-Tables, *Journal of the Royal Statistical Society. Series B (Methodological)*34, 187-220.

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.

Dewenter, K. L., P. H. Malatesta, 2001, State-owned and privately owned firms: an empirical analysis of profitability, leverage, and labor intensity, *American Economic Review* 91, 320-334.

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.

Faccio, M., R. W. Masulis, J. McConnell, 2006, Political connections and corporate bailouts, *The Journal of Finance* 61, 2597-2635.

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

Heimer, R. Z., 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 or http://dx.doi.org/10.2139/ssrn.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. M., 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.

La Porta, R., F. Lopez-de-Silanes, A. Shleifer, 2002, Government ownership of banks, *The Journal of Finance* 57, 265-301.

La Porta, R., F. Lopez-de-Silanes, A. Shleifer, 2006, What works in securities laws? *The Journal of Finance* 61, 1-32.

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.

Liao, L., Z. Wang, H. Xiang, X. Zhang, 2017, P2P Lending in China: An Overview.

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.

Lunde, A., A. Timmermann, D. Blake, 1999, The hazards of underperformance: A Cox regression analysis, *Journal of Empirical Finance* 6, 121-152.

Megginson, W. L., R. C. Nash, M. V. Randenborgh, 1994, The financial and operating performance of newly privatized firms: an international empirical analysis, *The Journal of Finance* 49, 403–452.

Minsky, H. P., H. Kaufman, 2008, Stabilizing an unstable economy, New York: McGraw-Hill.

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, 2009, Learning by trading, *Review of Financial Studies* 23, 705-739.

Shiller, R. J., 2013, Capitalism and financial innovation, *Financial Analysts Journal* 69, 21-25.

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

Sun, Q., W. H.S. Tong, 2003, China share issue privatization: the extent of its success, *Journal of Financial Economics* 70, 183-222.

Tang, H., 2018, Peer-to-peer lenders versus banks: substitutes or complements?

Van Horne, J. C., 1985, Of financial innovations and excesses. *The Journal of Finance* 40, 620-631.

Wei, Z., M. Lin, 2016, Market mechanisms in online peer-to-peer lending, *Management Science*, forthcoming.

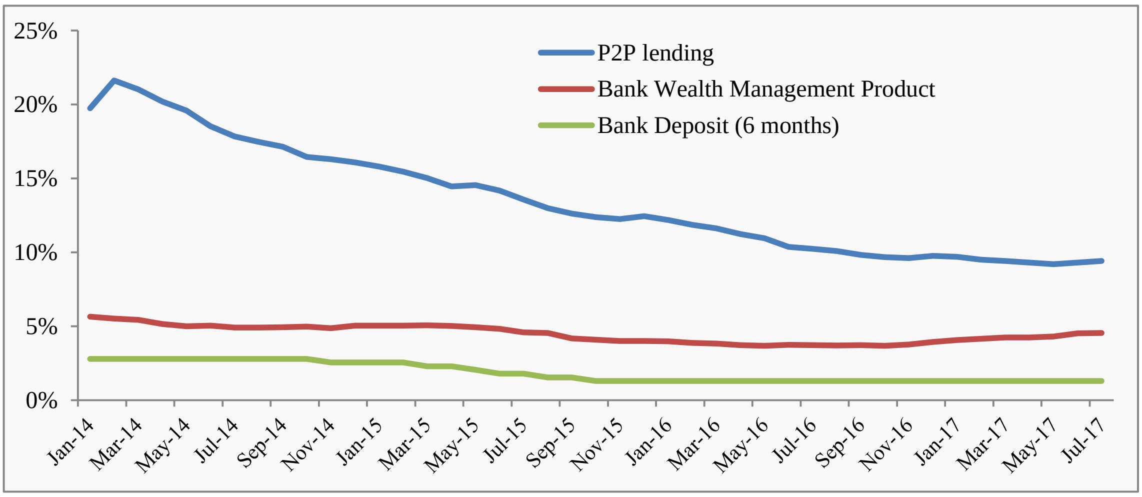
Zhu, N., 2016, China's Guaranteed Bubble, McGraw-Hill Education Press.

Figure I

Chinese P2P Lending Platforms and Interest Rates

Panel A illustrates the average interest rate for the P2P industry compared to the average rate on a bank CD and the average rate of return on wealth management products issued by commercial banks. The data are collected from www.wdzj.com and the data on banks are from WIND. The green line represents the interest rate for P2P lending, the red line represents the rate on bank CDs, and the blue line is for wealth management products. Panel B displays the pattern for the number of Chinese P2P platforms from 2012-16. The data are collected from “Home to P2P platforms” at www.wdzj.com. The total height for each month represents the total number of platforms that ever existed since 2012 to the respective month. The red bar represents the total number of defunct platforms since 2012 to the respective month. The blue bar represents the total number of surviving platforms since 2012 to the respective month.

Panel A. Annualized Percentage Rate on P2P Lending Compared to Other Investment Tools



Panel B. Number of Chinese P2P Platforms

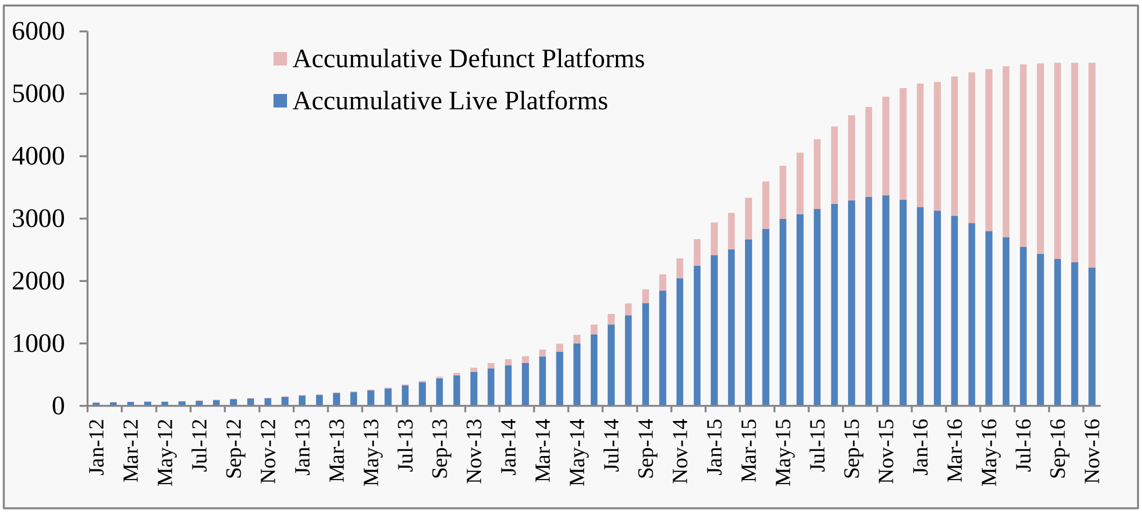


Table I

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 full sample, respectively. Panel C compares the trading sample with the full sample. Panel A presents summary statistics for the trading sample when we pool all platform-week observations together. The data are collected from the "Home to P2P platforms" at www.wdzj.com. The sample period is from January 2014 to July 2017. We require each platform to have at least 5 million CNY of registration capital. The following are dependent variables. *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. The following are control variables. *Size* is measured by the registered capital of the platform. *Age* is the number of years the platform has been in operation since its inception. *Term* is the weighted average term of loans from the platform weighted by each loan amount. *SOE* is a dummy variable with a value of one for platforms affiliated with SOEs and zero otherwise. Panel B presents summary statistics for the features of P2P platforms in the full sample. The full sample consists of 4,208 P2P platforms that existed from 2010 to 2016 in China. The data are collected manually from "Home to P2P platforms" at www.wdzj.com, and web.archive.org. We require each platform to have at least 5 million CNY registered capital. *Size* is measured by the registration capital of the platform. *Age* is the number of years the platform has been in operation between its inception and November 30, 2016. *Defunct* is a dummy variable taking a value of one for platforms ceasing to exist and zero for surviving platforms as of November 30, 2016. Panel C presents the features of platforms in the trading sample relative to those in the full sample. *Age* is the number of years the platform has been in operation between its inception and November 2016 for the full sample, or July 2017 for the trading sample. *Defunct* is a dummy variable taking a value of one for platforms ceasing to exist and zero for surviving platforms as of November 2016 for the full sample, or July 2017 for the trading sample. *** indicates the difference is different from zero at the 1% level and ** at the 5% level.

Panel A. Trading Sample (N=107,272)

	Mean	Std. Dev.	P1	P25	P50	P75	P99
SOE	0.086	0.280	0	0	0	0	1
Y variables							
Trading Volume (millions CNY)	27.467	73.820	0.043	1.210	4.061	15.700	514.576
Number of Investors	1,130.750	7,319.430	0	28	97	434	29,681
Number of Borrowers	224.874	11,013.120	1	1	4	19	10,835
Interest Rate (%)	12.934	9.315	5.6	9.76	12.14	15.13	31.69
Control variables							
Size / Registration Capital (millions CNY)	54.047	91.970	5	10	30	50.01	770
Age (years)	1.853	1.043	0.545	1.121	1.679	2.334	5.611
Term (years)	0.369	0.427	0.032	0.153	0.251	0.443	2.383

Panel B. Full Sample (N=4,208)

	Mean	Std. Dev.	P1	P25	Median	P75	P99
SOE	0.031	0.173	0	0	0	0	1
Size / Registration Capital (millions CNY)	43.514	48.463	5	10	30	50	300
Age (years)	1.338	0.967	0.005	0.551	1.262	1.934	4.115
Defunct	0.627	0.484	0	0	1	1	1

Panel C. NIFA sample (N=89)

	Mean	Std. Dev.	P1	P25	Median	P75	P99
SOE	0.157	0.366	0	0	0	0	1
Size / Registration Capital (millions 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

Table II

P2P Platforms 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 "Home to P2P platforms" at www.wdzj.com. The sample period is from January 2014 to July 2017. *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. *SOE* is a dummy variable with a value of one for platforms affiliated with SOEs and zero otherwise. *Term* is the weighted average term of loans from the platform weighted by each loan amount. *Age* is the number of years since the platform's inception. *Size* is measured by the registration capital of the platform. In all regressions, week fixed effects are included. Standard errors are clustered at both the platform and 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) Ln(Trading Volume)	(2) Ln(Number of Investors)	(3) Ln(Number of Borrowers)
SOE	0.706***	0.617***	0.067
	(5.280)	(3.006)	(0.390)
Ln(Size)	0.332***	0.462***	0.278***
	(8.713)	(8.291)	(6.043)
Ln(Age)	1.215***	1.898***	1.856***
	(8.487)	(9.409)	(8.203)
Ln(Term)	0.861***	0.721**	2.001***
	(4.599)	(2.352)	(6.715)
Week fixed effect	Y	Y	Y
Observations	107,272	107,272	107,272
R-squared	0.208	0.178	0.252

Table III

Platforms Failure Probability: Full Sample

This table presents the estimation results relating SOE affiliation and platform failure using the full sample. The full sample consists of 4,208 P2P platforms that existed sometime from 2010 to 2016 in China. The data are collected manually from "Home to P2P platforms" at www.wdzj.com, and web.archive.org. We require each platform to have at least 5 millions CNY of registration capital. Column (1) reports a probit model where construct a platform-week data using the full sample. The dependent variable *Defunct*, *i*s equal to one for platforms ceasing to exist at time *t* and zero for surviving platforms. The column headed "Marginal effect" reports the marginal effect of SOE affiliation on platform weekly failure, computed at the average value of the other explanatory variables. *SOE* is a dummy variable with a value of one for platforms affiliated with SOEs and zero otherwise. *Size* is measured by the registration capital of the platform. *Age* is the number of years the platform has been in operation since its inception and time *t*. Column (2) presents estimates of the determinants of the hazard rate to becoming a defunct platform using the following Cox-proportional hazard model.

$$h_i(t) = h_0(t)\exp(\delta_1 SOE_i + X_i'\delta)$$

The model includes one observation per each platform *i*. The baseline hazard function $h_0(t)$ measures the time until the platform failed (Defunct=1). $h_i(t)$ is the hazard ratio, the fraction of platforms operating prior to t relative to all 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.

	(1)		(2)	
	Probit (Defunct =1)		Cox analysis	
	Coefficient	Marginal effect	Coefficient	Hazard ratio
SOE	-0.777***	-1.732%	-2.413***	[0.090]
	(-8.947)		(-7.980)	
Ln(Size)	-0.071***		-0.191***	
	(-9.137)		(-9.011)	
Ln(Age)	-0.116***			
	(-5.900)			
Constant	-2.056***			
	(-73.252)			
Observations	297,789		4,208	
R-squared	0.010			

Table IV

P2P Platforms Performance and Stock Market Turbulence

This table presents results from the ordinary least squares regressions considering P2P platform performance and SOE background during the rising and falling periods of 2014-2016 in the Chinese stock market. The regression is using model (1) and the trading sample. The data are collected from "Home to P2P platforms" at www.wdzj.com. The rising period includes all weeks before the week of April 17, 2015. The falling period starts at the beginning of the week of April 17, 2015 to the end of June 2016. *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. *SOE* is a dummy variable with a value of one for platforms affiliated with SOEs and zero otherwise. *Term* is the weighted average term of loans of the platform weighted by each loan amount. *Age* is the number of years since the platform's inception. *Size* is measured by the registration capital of the platform. In all regressions, week fixed effects are included. Standard errors are clustered at both the platform and 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) Rising period (September 2014 to April 12,2015)			(2) Falling period (April 13,2015 to June 2016)		
	Ln(Trading Volume)	Ln(#Investors)	Ln(#Borrowers)	Ln(Trading Volume)	Ln(#Investors)	Ln(#Borrowers)
SOE	0.401**	0.493*	-0.309	0.685***	0.495**	-0.009
	(2.123)	(1.739)	(-1.509)	(4.573)	(2.082)	(-0.048)
Ln(Size)	0.392***	0.411***	0.274***	0.352***	0.505***	0.246***
	(6.560)	(4.348)	(3.639)	(7.963)	(7.787)	(4.634)
Ln(Age)	1.422***	2.229***	2.522***	1.309***	1.898***	1.954***
	(6.513)	(7.036)	(7.752)	(8.402)	(8.560)	(8.158)
Ln(Term)	0.399	0.461	1.831***	1.003***	0.640*	1.915***
	(1.480)	(1.011)	(4.630)	(4.721)	(1.729)	(5.144)
Week fixed effect	Y	Y	Y	Y	Y	Y
Observations	9,002	9,002	9,002	45,996	45,996	45,996
R-squared	0.266	0.190	0.357	0.211	0.157	0.229

Table V

P2P Platforms Survivals during Stock Market Turbulence

This table presents summary statistics for the characteristics of P2P platforms in the subsample. The platforms in the subsample are selected from the full sample, which were initiated before January 1, 2015 and are still alive at the beginning of April 2015. The subsample consists of 1,754 P2P platforms. The data are collected manually from "Home to P2P platforms" at www.wdzj.com, and web.archive.org. We require each platform to have at least 5 million CNY registration capital. Column (1) presents summary statistics for variables and Column (2) compares features for platforms affiliated with SOEs versus those not affiliated with SOEs. *SOE* is a dummy variable with a value of one for platforms affiliated with SOEs and zero otherwise. *Size* is measured by the registration capital of the platform. *Age* is the number of years the platform has been in operation between its inception and the end of June 2016 for surviving platforms and time to the cessation of operations for defunct platforms. *Defunct* is a dummy variable taking a value of one for platforms ceasing to exist and zero for surviving platforms as of the end of June 2016.

	Mean	Std. Dev.	P1	P25	Median	P75	P99	Non-SOE affiliated Platforms	SOE affiliated Platforms
			(N=1,754)					(N=1,677)	(N=77)
Size / Registration Capital (millions CNY)	41.625	50.408	5	10	20	50	300	41.002	55.190
Age (years)	1.848	0.815	0.364	1.458	1.762	2.170	4.838	1.831	2.226
Defunct	0.441	0.497	0	0	0	1	1	0.461	0
SOE	0.044	0.205	0	0	0	0	1		

Table VI

P2P Platforms Interest Rate and SOE Affiliation

This table presents results from the ordinary least squares regression of our baseline model (1). The data are collected from “Home to P2P platforms” at www.wdzj.com. The sample period is from January 2014 to July 2017. *Interest Rate (%)* is the weighted annualized percentage rate of the platform loans weighted by each loan amount. *SOE* is a dummy variable with a value of one for platforms affiliated with SOEs and zero otherwise. *Size* is measured by the registration 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. Week fixed effects are included. Standard errors are clustered at both the platform and 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	-2.220***
	(-6.691)
Ln(Size)	-0.498***
	(-4.750)
Ln(Age)	0.596*
	(1.811)
Ln(Term)	-4.896**
	(-2.445)
Week fixed effect	Y
Observations	107,272
R-squared	0.188

Table VII

P2P Platforms Profitability and SOE Affiliation

This table presents the results from the ordinary least squares regression relating to SOE backgrounds and platform efficiency using the NIFA data. The NIFA data consists financial data for 89 P2P platforms. The data are collected from the website of National Internet Finance Association of China (NIFA). We measure efficiency with Profit_POS, ROA, and Earnings Ratio. *Profit_POS* is a dummy variable taking value of one if a platform's 2016 earning is positive and zero otherwise. *ROA* is calculated as earnings over total assets. *Earnings Ratio* is calculated as earnings over total revenue. *SOE* is a dummy variable with a value of one for platforms affiliated with SOEs and zero otherwise. *Size* is measured by the registration capital of the platform. *Age* is the number of years since the platform's inception to the end of 2016 because the dependent variables here are all as of year 2016. Week fixed effects are included. Standard errors are clustered at both the platform and 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) Profit_POS	(2) ROA	(3) Earnings Ratio
SOE	0.347	-0.078	0.017
	(0.910)	(-0.871)	(0.030)
Ln(Size)	0.283*	0.074*	0.048
	(1.698)	(1.902)	(0.200)
Ln(Age)	0.041	0.029	-0.070
	(0.096)	(0.274)	(-0.111)
Observations	89	89	89
R-squared	0.0318	0.064	0.001

Table VIII
Potential Mechanisms

This table presents the ordinary least squares estimation results relating to platform performance and interest rates for platforms affiliated with certain types of SOEs. The data are collected from "Home to P2P platforms" at www.wdzj.com. The sample period is from January 2014 to July 2017. Panel A presents the results for platforms affiliated with central SOEs versus those affiliated with non-central SOEs using model (5). *CentralSOE* is equal to one if the platform is affiliated with a central government SOE and zero otherwise. *NCentralSOE* is equal to one if the platform is affiliated with a SOE but not a central government SOE and zero otherwise. Panel B presents the results for platforms affiliated with platforms affiliated with financial SOEs versus those affiliated with non-financial SOEs using model (6). *FinSOE* is equal to one if the platform is affiliated with a state-owned financial institution and zero otherwise. *NFinSOE* is equal to one if the platform is affiliated with a SOE but no financial institution is in its ultimate shareholders 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. *Size* is measured by the registration 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 weighted by each loan amount. In all regressions, week fixed effects are included. Standard errors are clustered at both the platform and 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.

Panel A. P2P Platforms Performance and Central-SOE Affiliation

	(1)	(2)	(3)	(4)
	Ln(Trading Volume)	Ln(#Investors)	Ln(#Borrowers)	Interest Rate (%)
CentralSOE	1.069***	1.171***	0.676*	-2.645***
	(3.779)	(2.750)	(1.656)	(-4.835)
NCentralSOE	0.586***	0.434*	-0.136	-2.118***
	(4.106)	(1.944)	(-0.806)	(-5.451)
Ln(Size)	0.331***	0.462***	0.278***	-0.496***
	(8.753)	(8.322)	(6.096)	(-4.733)
Ln(Age)	1.207***	1.885***	1.843***	0.604*
	(8.330)	(9.242)	(8.051)	(1.838)
Ln(Term)	0.855***	0.712**	1.990***	-2.363***
	(4.609)	(2.346)	(6.787)	(-5.365)
Week fixed effect	Y	Y	Y	Y
Observations	107,272	107,272	107,272	107,272
R-squared	0.209	0.179	0.256	0.188

Panel B. P2P Platforms Performance and Financial-SOE Affiliation

	(1) Ln(Trading Volume)	(2) Ln(#Investors)	(3) Ln(#Borrowers)	(4) Interest Rate (%)
FinSOE	1.654***	1.197**	0.957**	-3.462***
	(5.989)	(2.087)	(2.009)	(-6.054)
NFinSOE	0.517***	0.502**	-0.111	-2.007***
	(3.727)	(2.392)	(-0.652)	(-5.496)
Ln(Size)	0.334***	0.463***	0.280***	-0.499***
	(8.864)	(8.364)	(6.159)	(-4.762)
Ln(Age)	1.240***	1.913***	1.880***	0.563*
	(8.759)	(9.528)	(8.364)	(1.725)
Ln(Term)	0.825***	0.699**	1.967***	-2.323***
	(4.516)	(2.317)	(6.790)	(-5.263)
Week fixed effect	Y	Y	Y	Y
Observations	107,272	107,272	107,272	107,272
R-squared	0.215	0.179	0.256	0.189

Appendix.

Table A1. Definition of variables

Variable	Symbol	Description
		Panel A: SOE Affiliation
SOE	SOE	A dummy variable with a value of one for platforms affiliated with SOEs and zero otherwise. We identify platforms affiliated with SOEs by checking the platform's shareholders. Note that we identify platforms with a SOE affiliation only when the platform was supported since the platform's inception.
CentralSOE	CentralSOE	A dummy variable with a value of one if the platform is affiliated with a central government SOE and zero otherwise. We identify central SOE affiliation when the State Council, the Chinese central government, is among its ultimate shareholders.
NCentralSOE	NCentralSOE	A dummy variable with a value of one if the platform is affiliated with a SOE but not a central government SOE and zero otherwise.
FinSOE	FinSOE	A dummy variable with a value of one if the platform is affiliated with a state-owned financial institution, such as a bank, an insurance company or an asset management company, and zero otherwise.
NFinSOE	NFinSOE	A dummy variable with a value of one if the platform is affiliated with a SOE but no financial institution is in its ultimate shareholders and zero otherwise.
		Panel B: Platform Performance
Trading volume	Ln(Trading Volume)	The natural log of the weekly trading volume of a platform. Volume is measured in CNY, winsorized at the 1% and 99% level.
Number of Investors	Ln(Number of Investors)	The natural log of the total number of investors during a given week for a given platform, winsorized at the 1% and 99% level.
Number of Borrowers	Ln(Number of Borrowers)	The natural of the total number of borrowers during a given week for a given platform, winsorized at the 1% and 99% level.
Interest Rate (%)	Interest Rate (%)	The annualized rate of return for the platform loans during the week for a given platform, weighted by each loan amount. Interest Rate is measured in annual percentage terms and winsorized at the 1% and 99% level.
		Panel C: Platform Features
Size	Ln(Size)	The natural log of the registration capital of the platform,

		winsorized at the 1% and 99% level.
Age	Ln(Age)	The natural log of how old a platform is at the end of this week since its initiation date. Age is measured in years.
Term	Ln(Term)	The natural log of the weighted average term during the week for a given platform, weighted by each loan amount. Term is measured in years.

Table A2. Comparison between SOE Platforms and non-SOE platforms

This table compares features for platforms affiliate with SOEs versus those not in the trading sample. Panel A and B present summary statistics for the trading sample and full sample, respectively. Panel A presents summary statistics for the trading sample when we pool all platform-week observations together. The data are collected from "Home to P2P platforms" at www.wdzj.com. The sample period is from January 2014 to July 2017. We require each platform to have at least 5 million CNY registration capital. The following are dependent variables. *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. The following are control variables. *Size* is measured by the registration capital of the platform. *Age* is the number of years the platform has been in operation since its inception. *Term* is the weighted average term of loans of the platform weighted by each loan amount. Panel B presents summary statistics on the characteristics of P2P platforms in the full sample. The full sample consists of 4,208 P2P platforms that existed sometime during 2010 to 2016 in China. The data are collected manually from "Home to P2P platforms" at www.wdzj.com, and web.archive.org. *Age* is the number of years the platform has been in operation between its inception and November 30, 2016. *Defunct* is a dummy variable taking a value of one for platforms ceasing to exist and zero for surviving platforms as of November 30, 2016. *** indicates the difference is different from zero at the 1% level and ** at the 5% level.

Panel A. Trading Sample (N=107,272)

	Non-SOE Platforms	SOE Platforms	p-value for difference
Y variables			
Trading Volume (millions CNY)	25.986	43.282	0.000***
Number of Investors	1,090.250	1,563.060	0.000***
Number of Borrowers	231.691	202.851	0.012**
Interest Rate (%)	13.166	10.462	0.000***
Control variables			
Size / Registration Capital (millions CNY)	53.229	62.778	0.000***
Age (years)	1.841	1.976	0.000***
Term (years)	0.361	0.453	0.000***

Panel B. Full Sample (N=4,208)

	Non-SOE Platforms	SOE Platforms	p-value for difference
Size / Registration Capital (millions CNY)	40.860	58.484	0.000***
Age (years)	1.312	2.145	0.000***
Defunct	0.645	0.085	0.000***

Table A3. Defunct cases distribution

For the 2,639 defunct platforms in the full sample, we put them into 3 categories. 40% of defunct platforms were a form of Ponzi scheme and 17% of them failed due to poor operation or performance. For the remaining 43% of defunct platforms, we could not easily tell why they failed.

Categories	**N**	**Percent**
Fraudulent Platform (i.e. Ponzi Scheme)	1,052	39.86%
Operational or Performance Failures	463	17.54%
Do not know	1,124	42.59%
Total	2,639	100%