Government Affiliation and Peer-To-Peer Lending Platforms in China[l]

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

PBC School of Finance, Tsinghua University, PR China

ARTICLE INFO

ABSTRACT

With thousands of co-existing and competing platforms, the Chinese peer-to-peer (P2P) lending market experienced both high growth and high failure rate. We hand collect unique data for these P2P platforms and investigate the differences in performances and survivals for platforms with and without affiliations with state-owned enterprises (SOEs). P2P platforms with SOE affiliations have higher trading volumes, attract more investors, and offer lower interest rates. These platforms also survive significantly better than those without the SOE affiliations, especially during market downturns. Using P2P platforms with fake SOE affiliations as identification, we show that the SOE affiliation itself (not related to the fundamentals) is an important signal for P2P market participants. These results can be helpful to investors and regulators, especially those from other emerging markets.

1. Introduction

Peer-to-peer (P2P) lending, the practice of directly matching lenders and borrowers through online services, was first introduced in China in 2007. Over the 10 years between 2008 and 2018, the Chinese P2P market enjoyed phenomenal growth and became an important component of the financial industry. By early 2018, around 6,000 P2P platforms had been established in China, facilitating loans in the amount of around $800 billion. This tremendous growth has been accompanied by a phenomenally high failure rate. By early 2018, over 60% of the 5,000 + P2P platforms that ever operated were closed. As a result of nation-wide tightening regulations on P2P platforms over 2018 to 2020, only 29 online lending platforms are still operating by June 2020. The substantial industry size, large cross section of platforms, the extremely high failure rate and dramatic regulation changes all clearly separate the Chinese P2P market from the P2P markets from developed countries,[1] which also makes it a fascinating research subject.

One potential driver for the rapid growth of P2P platforms in China is the under-development of the economic infrastructure, including the traditional banking sector, the credit system, and the law enforcement system, which possibly leaves space for the fast growth of financial innovations such as P2P platforms. On the other hand, the under-development of the economy can also lead to many uncertainties and even systemic risks for financial innovations such as P2P platforms. In this situation, the government's guidance and regulation on the P2P platforms can be essential. Interestingly, many Chinese P2P platforms advertise prominently

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

on their websites that they are affiliated with the government, or state-owned enterprises (SOEs), indicating that these platforms possibly believe that SOE affiliations can help them to attract potential customers. In this paper, we study the development and dynamics of the overall Chinese P2P market by investigating how government affiliations are related to the performances and survival dynamics of thousands of P2P lending platforms in China.

To the best of our knowledge, few if any previous studies examine the cross section of P2P platforms, possibly because there are no available public data on multiple P2P platforms. Given that the history of the industry is short, the nature of the business is private, and regulators have not requested the P2P platforms to submit their operational data, it is quite difficult to obtain relevant and direct data on multiple P2P platforms. To overcome the data difficulty, we hand collect data on thousands of P2P platforms, with substantial cross-sectional variations in government affiliations and platform performance measures. To be specific, we collect two datasets. The first dataset contains detailed weekly transaction data at the platform level for 1,593 P2P platforms from January 1, 2014 to February 28, 2018. The second dataset contains survival information for over 5,000 platforms, which covers almost all of the P2P platforms that existed between 2012 and 2018. We stop in 2018 because the data sources cease to exist after mid-2018, when the whole industry went through major contraction. That is, our study focuses on the uprising expansion period of the P2P industry in China. These novel datasets allow us to closely examine important issues such as cross-platform performances and survivals, which have been difficult for previous studies to investigate. Unfortunately, P2P platforms mostly do not disclose information about individual loans, or information regarding their routine operations. Therefore, our data also do not have this detailed information.

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

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

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

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

Our paper naturally connects to the growing literature on P2P lending market. This strand of literature primarily focuses on how a borrower's information (e.g., Pope and Sydnor, 2011; Duarte et al., 2012; Lin et al., 2013; Iyer et al., 2015) and market designs (Hildebrand et al., 2017; Wei and Lin, 2017; Hertzberg et al., 2018) affect lender behaviors, funding outcomes, and borrowers' performances. Different from our study, the above studies mostly focus on information processing using data from a single U.S. based platform. To the best of our knowledge, we are the first study to examine performances and survivals 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 new industry.

Recently, researchers have also studied the relation between P2P platforms and traditional financial institutions, such as commercial banks (Tang, 2019) and institutional investors (Vallee and Zeng, 2019). Many papers, such as Bartlett et al. (2018),

---

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

Buchak et al. (2018), Chen et al. (2019), Fuster et al. (2019), examine the advantage of fintech over traditional financial services providers. Unlike these studies, which are all based on data from developed countries, our research focuses on the largest emerging market with an under-developed banking, credit and law enforcement system, and thus provides a new perspective on how fintech firms grow and mature in an emerging market, as well as the associated benefits and costs.

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

The remainder of this article is organized as follows. In Section 2, we introduce the institutional background of the Chinese P2P market. Data are discussed in Section 3. Section 4 provides the basic empirical results on the relation between government affiliations and platform performances and survival probabilities. We discuss the identification issue using platforms with fake SOE affiliations in Section 5. In Section 6, we provide evidence on potential channels for the positive correlations between SOE affiliations and platform performances and survivals. Section 7 concludes.

2. China P2P platforms: Institutional background

The P2P market is first introduced in the developed markets, which have more efficient financial sectors, more mature credit score systems, and more effective law enforcement than the emerging markets do. In the existence of mature banking and investment sectors,

Given the fierce cross-platform competition for visitor traffic and survival, some platforms have begun to adopt the practice of ``principal guarantee''; this practice quickly has become prevalent among all P2P platforms. The ``principal guarantee'' means that the platform guarantees to payback principal to investors in the event of default by borrowers. Typical P2P platforms in most of the other countries, such as the U.S., only serve as an intermediary for connecting the borrowers and the lenders. When borrowers default, lenders bear the losses, which has no impact on the platform. For Chinese P2P platforms, however, when borrowers default, under ``principal guarantee'', the platform promises to return the principal back to the lenders. Therefore, the platform, not the lender, bears (most of) the consequence of borrowers' default, and the majority of the credit risk exposure (at least the principal part) is shifted from individual investors to platforms.

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

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

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

3. Data

Most existing studies on P2P platforms use data from the U.S., and they typically only examine one platform, mostly Prosper.com, which makes data publicly available. For multiple P2P platforms, because no regulation requires them to make the data publicly available, data are hard to obtain. For our study, we hand collect the data items. In Section 3.1, we introduce our measure for government affiliation. The datasets for performances and survivals are discussed in Section 3.2, Section 3.3 provides summary statistics.

3.1. SOE affiliations

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

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

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

---

[5] In Appendix B, we provide more detailed discussions on government regulations and guidance for the industry over 2015 to 2020.

3.2. P2P platform performances and survivals

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

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

Our second dataset contains the life cycle information of thousands of Chinese P2P platforms, and we refer to this sample as the ``long sample''. As mentioned earlier, from 2011 to 2018, around 6,000 platforms came into existence in this market, and over 3,000 platforms ended in failure. Before this study, no existing database had aggregated the information on the life cycles of these platforms. We first collect the platforms' names from www.wdzj.com, and www.p2peye.com, (the second largest online information provider for P2P platforms in China but without trading information), and then hand collect the life cycle information from the platforms' homepages and the public press For detailed information of defunct platforms, we cross check their historical information via web.archive.org, a U.S.-based website taking snapshots of public websites automatically. The data items collected include platform name, inception date, amount of capital at time of registration, holding structure, and failure date (when applicable). We obtain information for 5,498 platforms, which covers majority of the P2P platforms that have existed since 2011. To exclude platforms with insignificant market sizes, we require each platform to have at least 5 million Chinese Yuan in registered capital. This filter leaves a sample of 4,210 platforms.[6]

3.3. Summary statistics on key variables

We first compute the summary statistics for a dummy variable *SOE*, which takes the value of one if a P2P platform is affiliated with an SOE, and zero otherwise. In our pooled trading sample, 8.9% of the platform $\times$ week observations are from platforms with SOE affiliations.

Next we present summary statistics of the pooled trading sample in Table 1 Panel A. To facilitate direct comparison between SOE and non-SOE platforms, we report the statistics of platform performance measures for platforms with SOE affiliations in the left half panel and platforms without SOE affiliations in the right half panel. Since platform income is mostly from loan origination fees and account service fees, which are not reported but are largely based on platform transaction volumes, we use trading volumes and number of borrowers/investors as performance measures for the P2P platforms. All information is aggregated at the platform level each week, so we do not have individual loans information.

We measure *Trading Volume* as the weekly total amount of new loans funded. For *Trading Volumes*, the mean values for platforms with SOE affiliations and for platforms without SOE affiliations are 44 and 27 million Chinese Yuan, respectively. For *Number of Investors*, the mean values for platforms with SOE affiliations and those without are 1,627 and 1,141 each week. For *Number of Borrowers*, the mean values for platforms with SOE affiliations and those without are 305 and 208, respectively. That is to say, the SOE platforms have higher trading volumes, larger numbers of investors and borrowers than the non-SOE platforms do.

To better understand how the trading volumes and number of investors evolve over time, we present the time series of average weekly trading volumes and numbers of investors for SOE-affiliated platforms and non-SOE-affiliated platforms for the trading sample platforms in Fig. 1. Interestingly, the SOE-affiliated P2P platforms enjoy larger and gradual increases over the period of 2015 to 2017, in terms of both trading volumes and number of investors, than the non-SOE-affiliated platforms do. The platforms without SOE affiliations, on the other hand, also have increased volumes and number of investors, while the increases mostly happen in 2017. Clearly, the SOE-affiliated platforms attract most of the investors during the beginning of the quick expansion period of the P2P industry in 2015. The non-SOE affiliated platforms catch up with the SOE affiliated platforms in 2017, possibly because investors are more familiar and comfortable with the business model of P2P platforms.

The trading data also provide weekly platform-level *Interest Rate*, which is computed as a loan amount-weighted average of the annualized percentage return rate of all facilitated loans for the platform during the week. The interest rate is what the platform offers to investors. As discussed earlier, the interest rates at Chinese P2P platforms are preset and directly offered to investors. Therefore, these rates possibly reflect both the platform's risk assessment and investor's risk appetite. The mean interest rate offered by P2P platforms with SOE affiliations is 10.4%, and the mean interest rate offered by P2P platforms without SOE affiliations is

---

[6] While the long sample has a greater coverage of all platforms, the trading sample contains the largest and the most active platforms, and we need to be cautious that results using the trading sample might be biased toward the larger and more active platforms. Meanwhile, to examine the coverage of the trading sample platforms, we compute the total trading volume of the whole P2P lending market (as in the long sample) in 2017, and find that trading sample P2P platforms accounts for 90% of the total transaction volume, which indicates that the trading sample's coverage of the whole P2P industry is adequate.

Table 1

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

Panel A. Trading sample				
	(1)	(2)	(3)	(4)
	SOE platforms (N = 11,452)		Non SOE platforms (N = 117,221)	
	Mean	Median	Mean	Median
Y variables				
Trading volume (million CNY)	44.383	14.200	27.462	3.970
Number of investors	1,627	297	1,141	93
Number of borrowers	306	8	284	5
Interest rate (%)	10.395	9.890	12.848	12.000
Control variables				
Size/Registered capital (million CNY)	62.023	50.000	53.261	30.000
Age (years)	2.228	1.984	2.058	1.882
Term (years)	0.453	0.338	0.372	0.255
Panel B. Long sample				
	(1)	(2)	(3)	(4)
	SOE platforms (N = 130)		Non SOE platforms (N = 4,080)	
	Mean	Median	Mean	Median
Size/Registered capital (million CNY)	58.484	50.000	40.841	21.900
Age (years)	3.256	3.221	1.746	1.419
Defunct	0.123	0.000	0.661	1.000

12.8%. The interest rate offered by P2P platforms are much higher than those offered by bank deposits and wealth management products.

For basic platform characteristics, we later use the registered capital of a platform as a proxy for its size. The mean registered capitals of the platforms with SOE affiliations are 62 million Chinese Yuan, while the mean registered capitals of the platforms without SOE affiliations are 53 million Chinese Yuan. Compared to traditional loan providers, such as commercial banks, average P2P platforms are relatively small.

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 average age of P2P platforms with SOE affiliations is 2.23 years and that of P2P platforms without SOE affiliations is 2.06 years. The P2P platforms in general 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 terms for SOE-affiliated platforms and non-SOE-affiliated platforms are 0.453 and 0.372 years, or namely, approximately 5.4 and 4.5 months, respectively. The overall pattern indicates that Chinese P2P lending platforms mostly facilitate short-term loans.

We also compare median values of platform performances and control variables for those with SOE affiliations and those without. The pattern is very similar to that of the means. We also notice that the mean values are significantly higher than median values, indicating that most of variables display positive skewness. Therefore, in later empirical testing, we use the natural logarithm of these variables except interest rates.

Table 1 Panel B reports the summary statistics of the long sample. In our long sample, 130 (3.1%) of the total 4,210 platforms have an SOE affiliation. For other platform characteristics, we show mean and median values by SOE affiliations. SOE-affiliated platforms have average registered capital of 58 million Chinese Yuan, while non-SOE-affiliated platforms have 41 million. The mean ages for the SOE-affiliated platforms and non-SOE platforms are 3.256 and 1.746 years, respectively.

More importantly, we compute variable *defunct* as a dummy variable, taking a value of one when the platform ceases to exist as of February 2018, the ending date of data collection, and zero otherwise. We find that 16 SOE-affiliated platforms (12.3% of SOE-affiliated platforms) and 2697 non-SOE-affiliated platforms (66.1% of non-SOE-affiliated P2P platforms) became defunct as of February 2018. These numbers imply that P2P lending platforms are highly risky, especially for platforms without SOE affiliations. The median value comparison for these characteristics shows similar pattern.
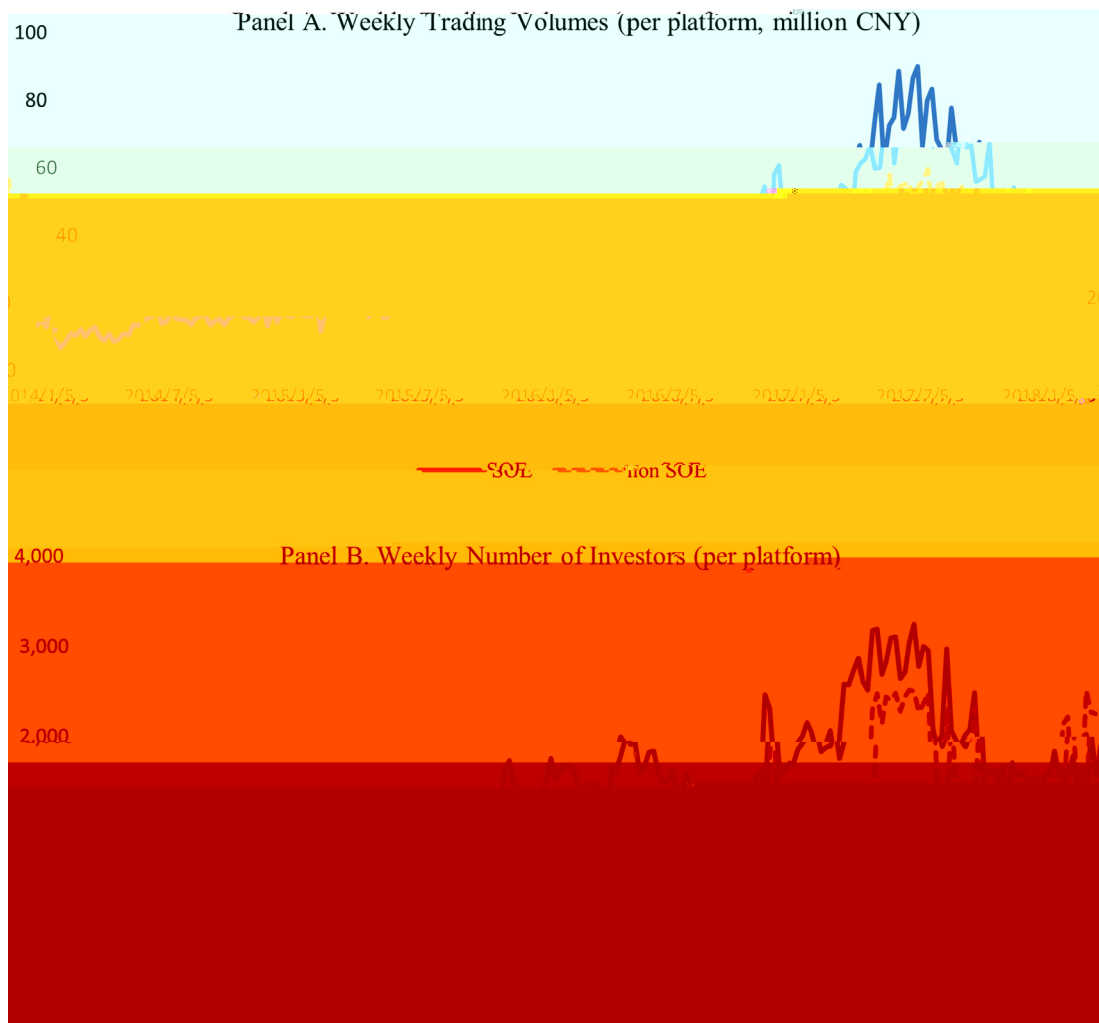
Fig. 1. Platform traffic evolvement. This figure illustrates the pattern for platform traffics by SOE affiliation. The data are collected from www.wdzj.com. The sample period is from January 2014 to February 2018. Panel A shows the weekly trading volumes per platform for SOE-affiliated platforms and non-SOE-affiliated platforms. Panel B shows the average number of investors per platform for SOE-affiliated platforms and non-SOE-affiliated platforms.

4. Main results

In this section, we examine how P2P platforms with and without SOE affiliations differ. We first study the relation between SOE affiliations and P2P performances using the trading sample in Section 4.1. In Section 4.2, we link a platform's affiliation to its survival in the long sample. Finally, we compare interest rates offered by P2P platforms with and without SOE affiliations using the trading sample in Section 4.3.

4.1. SOE affiliations and performances

It is unclear how government affiliations are related to P2P platform performances. Rajan and Zingales (2004) state that at the early stage of a financial market, government can be useful in establishing the market rules as a central authority, which implies that the government might play a positive role in shaping financial innovation. In addition, Acharya and Kulkarni (2019) find that government affiliation can be especially important during a financial crisis, using the Indian banking system data during the 2007 2009 global financial crisis. They find that public banks had a higher deposit and credit growth than private banks, and experienced an increase in confidence, as investors believed that their downside risk was minimized because of the implicit government guarantee. Acharya and Kulkarni (2019) further note that the government guarantees facilitate state-owned banks in obtaining access to inexpensive credit and thus, state-owned banks in India outperform private sector banks during a crisis. In the context of China, Kornai (1986), Boyreau-Debray and Wei (2005), Lu et al. (2005), and Song et al. (2011) determine SOEs are more likely to obtain external financing from banks and enjoy soft-budget constraints that help protect their business.

Table 2

P2P platform performance and SOE affiliation. This table presents the results of the ordinary least squares regression for our baseline model (1). The data are collected from www.wdzj.com. The sample period is from January 2014 to February 2018. *Trading Volume* is the total funding facilitated on the platform. *Number of Investors* is number of investors on the platform. *Number of Borrowers* is number of borrowers on the platform. *SOE* is a dummy variable with a value of one for platforms affiliated with SOEs and zero otherwise. *Size* is measured by the registered capital of the platform. *Age* is the number of years since the platform *i*'s inception to time *t*. *Term* is the weighted average term of loans from the platform weighted by each loan amount. In all regressions, province fixed effects and week fixed effects are included. Standard errors are clustered at both the platform and the week level. T-statistics are reported in parentheses. *** indicates the coefficient is different from zero at the 1% level, ** at the 5% level, and * at the 10% level.

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

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

$$\text{Performance}_{it} = \ + \ \times \text{SOE}_i + \ \times \text{Control}_{it} + \text{Province}_i + \text{Week}_t + "_{it}. \tag{1}$$

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

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

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

Table 2 reports the estimation results on how SOE affiliation is related to our three performance measures. In the first regression for trading volume, the coefficient on SOE is 0.775 with a t-statistic of 6.146. In other words, an SOE-affiliated platform has 117.06% ($= e^{0.775} - 1$) more trading volume on average than a non-SOE-affiliated platform. In the second regression for number of investors, the coefficient on SOE is 0.814, with a significant t-statistic of 4.192. Economically, a SOE-affiliated platform attracts 125.69% ($= e^{0.814} - 1$) more investors than a non-SOE-affiliated platform does on average. For the third regression for number of borrowers, the coefficient on SOE is 0.178, with an insignificant t-statistic of 1.056. In terms of magnitude, an SOE-affiliated platform has 19.48% ($= e^{0.178} - 1$) more borrowers than a non-SOE-affiliated platform on average.

It is perhaps not surprising that the SOE affiliation is more important for investors than borrowers. For investors, given the

Table 3

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

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

the SOE affiliation does not significantly affect the number of borrowers. In future tables, we most focus our discussion on number of investors rather than number of borrowers.

The coefficients on the control variables are all significant and carry the expected signs. Larger platforms and older platforms tend to have higher trading volumes and attract more investors and borrowers. Interestingly, platforms with longer term loans tend to attract more traffic. The R^2s for all three regressions are approximately 25%. Our findings in Table 2 show that platforms with SOE affiliations are more likely to attract higher trading volumes, more investors, and more borrowers.[7]

4.2. SOE affiliations and survivals

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

$$h_i(t) = h_0(t) \exp(\times SOE_i + \times Control_i + Province_i); \qquad (2)$$

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

We report the Cox analysis results in Table 3. The coefficient on the *SOE* variable is −2.055, with a significant t-statistic of −8.172, with the standard errors clustered by platform as in Heimer (2016). The negative sign indicates that SOE affiliation significantly reduces the conditional default probability of P2P platforms. In economic terms, the hazard ratio of $0.128 = \exp(-2.055)$ indicates that during the sample period (from 2014 to Feb 2018), the conditional failure probability for P2P platforms with SOE affiliation is only 12.8% of that for P2P platforms without SOE affiliation. In other words, P2P platforms with SOE affiliation are, on average, 87.2% less likely to default than those without SOE affiliation. The coefficients on the size variable is negative and significant, indicating that larger platforms survive longer.

As in Acharya and Kulkarni (2019), government affiliation can be especially important during financial crises. If the investors believe that the SOEs would protect the affiliated P2P platforms from failing, they would not abandon the SOE-affiliated platforms, and these platforms are more likely to survive. The recent Chinese stock market turbulence over year 2014 and 2015 provide an excellent opportunity to investigate the survival pattern of the P2P platforms. Between June 2014 and June 2015, the Shanghai Stock Exchange Composite Index (SSECI) first surged by approximately 110%. In early July 2015, however, the SSECI plummeted by 32%, destroying more than 18 trillion Chinese Yuan in share value, according to Huang et al. (2016). On August 24, 2015, the SSECI fell by another 8.48%, marking the largest single day fall since 2007. From October 2015 to the end of our sample, the market slowly recovered.

We directly investigate the defunct probabilities of various P2P platforms from June 2015 to June 2016. In this exercise, we require the platforms to be founded before January 1, 2015 to have an adequate number of time series observations for each platform when market turbulence occurs. Our sample contains 1754 platforms, of which 77 are SOE-affiliated. As of June 2016, 773 platforms, or 44.1% of all platforms in this sample, ceased to exist, yet *none* of these 773 defunct platforms are affiliated with SOEs. This distinctive pattern provides strong evidence that SOE-affiliated platforms are much less likely to default than non-SOE platforms during market turmoil.[8]

---

[7] We conduct two robustness checks, and results are reported in Appendix C. First, to better control for size, we match each SOE affiliated platform with three similar-sized platforms without SOE affiliation, and re-estimate the panel regression. Second, we use monthly data rather than weekly data. The results are quite similar to those in Tables 2 4. In both cases, SOE-affiliated platforms have higher trading volumes, number of investors, and survival probabilities and lower interest rates than non-SOE-affiliated platforms.

[8] Following one of the referees' suggestion, we also look at measures for macroeconomic conditions and examine the survival pattern of platforms during the economic downturns. We measure economic conditions with GDP growth rate, urban household income growth rate, and registered unemployment rate. The

Table 4

P2P platform interest rate and SOE affiliation. This table presents the results from the ordinary least squares regression of model (3). The data are collected from www.wdzj.com. The sample period is from January 2014 to February 2018. *Interest Rate (%)* is the weighted annualized percentage rate of the platform loans weighted by each loan amount, which is offered to investors. *SOE* is a dummy variable with a value of one for platforms affiliated with SOEs and zero otherwise. *Size* is measured by the registered capital of the platform. *Age* is the number of years since the platform's inception. *Term* is the weighted average term of loans of the platform by each loan amount. Province fixed effects and week fixed effects are included. Standard errors are clustered at both the platform and the week level. T-statistics are reported in parentheses. *** indicates the coefficient is different from zero at the 1% level, ** at the 5% level, and * at the 10% level.

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

4.3. SOE affiliation and interest rate

Interest rates are key variables for P2P loans. As discussed earlier, most P2P platforms provide principal guarantee, and bear most of the default risks from borrowers. As a result, the P2P platforms preset the interest rates for investors.[9] If SOE affiliation is

Table 5

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

Panel A. Summary statistics for platforms with Fake SOE affiliations					
	(1)	(2)	(3)	(4)	(5)
	Fake SOE platforms	SOE platforms	Non-SOE platforms	p-value for diff. (2) (1)	p-value for diff. (3) (1)
Registered capital (million CNY)	51.526	62.917	53.247	0.000***	0.238
Age (years)	2.594	2.225	2.074	0.000***	0.000***
Term (years)	0.380	0.460	0.374	0.000***	0.247

Panel B. Fake SOE Affiliation vs. Non SOE Affiliation, matched sample			
	(1) Ln(Trading volume)	(2) Ln(#Investors)	(3) Platform failure probability
FakeSOE	0.740**	1.135**	−3.837%***
	(2.237)	(2.123)	(−18.893)
Week FE	Y	Y	Y
Observations	4,612	4,612	6,323
R-squared	0.168	0.097	0.502

Panel C. Revelation of fake SOE Affiliation and platform performance, matched sample		
	(1) Ln(Trading volume)	(2) Ln(#Investors)
FakeSOE	0.728**	1.103**
	(2.195)	(2.048)
FakeSOE × After	−0.806***	−0.757*
	(−4.648)	(−1.829)
After	0.554***	0.283
	(4.542)	(0.768)
Observations	4,764	4,764
R-squared	0.205	0.177

We are able to identify eleven platforms with fake affiliations with CNNC, consisting of 1499 observations in the trading sample, equivalent to over 13% of real SOE affiliated platforms observations. We define *FakeSOE* as a dummy variable, taking the value of one when a platform fakes its SOE affiliation, and zero otherwise.

We first compare platforms with fake SOE affiliations to other platforms. From Panel A of Table 5, we find that the platforms with fake SOE affiliations are significantly smaller than platforms with true SOE affiliations and are not significantly different from platforms without SOE affiliations. Interestingly, platforms with fake SOE affiliations survive longer, by a few months, than platforms with true SOE affiliations and no SOE affiliations.

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

$$Performance_{it} = + \times FakeSOE_i + Week_t + "_{it}: \tag{4}$$

We restrict the sample to the week before the revelation. In the first regression for trading volume of Table 5 Panel B, the coefficient on $FakeSOE$ is 0.740 with a t-statistic of 2.237. In other words, a platform with fake SOE affiliation on average has 109.59% ($= e^{0.740} − 1$) more trading volume than matched non-SOE-affiliated platforms do. In the second regression for number of investors, the coefficient on $FakeSOE$ is 1.135, with a significant t-statistic of 2.123. Economically, a fake-SOE-affiliated platform attracts 211.12% ($= e^{1.135} − 1$) more investors than other non-SOE platforms do on average. The above results suggest that the title of ``SOE affiliation'' itself could attract more traffic for P2P platforms, even though it is fake.

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

$$Pr(Defunct_{it}) = (+ \times FakeSOE_i + Week_t + "_{it}): \tag{5}$$

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

From the last column in Table 5 Panel B, for convenience of economic interpretation, we report marginal effect of *FakeSOE*, which is −3.837% with a significant t-statistic of −18.893. That is, the P2P platforms with fake SOE affiliations have a weekly

failure rate that is 3.837% (or an annual failure rate that is 86.93% = 1-(1 3.837%)[52]) less than that of other non-SOE-affiliated P2P platforms. In other words, the platforms with fake SOE affiliations are significantly more likely to survive than other platforms with no SOE affiliations.[11]

5.2. Revelation of fake SOE affiliations

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

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

Table 6

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

$$Pr(Defunct_{it}) = (+ \times FinSOE_i + \times NFinSOE_i + \times Control_{it} + Province_i + Week_t + "_{it}):$$

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

Panel A. P2P Platform performance and central-SOE affiliation					
	(1) Ln(Trading volume)	(2) Ln(#Investors)	(3) Ln(#Borrowers)	(4) Interest rate (%)	(5) Probit (Defunct = 1)
CentralSOE	1.027***	1.417***	0.713*	−2.005***	−3.541%***
	(3.644)	(3.688)	(1.801)	(−4.470)	(−54.624)
NCentralSOE	0.697***	0.629***	0.013	−2.174***	−0.693%***
	(5.293)	(2.939)	(0.077)	(−5.914)	(−8.174)
Controls, Province FE, Week FE	Y	Y	Y	Y	Y
Observations	128,673	128,673	128,673	128,673	397,617
R-squared	0.285	0.219	0.274	0.275	0.104

Panel B. P2P Platform performance and financial-SOE affiliation					
	(1) Ln(Trading volume)	(2) Ln(#Investors)	(3) Ln(#Borrowers)	(4) Interest rate (%)	(5) Probit (Defunct = 1)
FinSOE	1.483***	1.353**	0.926*	−2.653***	−3.665%***
	(5.374)	(2.504)	(1.905)	(−4.777)	(−48.109)
NFinSOE	0.652***	0.721***	0.048	−2.044***	−0.710%***
	(4.978)	(3.617)	(0.285)	(−6.030)	(−8.292)
Controls, Province FE, Week FE	Y	Y	Y	Y	Y
Observations	128,673	128,673	128,673	128,673	397,617
R-squared	0.287	0.218	0.274	0.275	0.104

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

$$Pr(Defunct_{it}) = (+ \times CentralSOE_i + \times NCentralSOE_i + \times Control_{it} + Province_i + Week_t + "_{it}): \qquad (8)$$

The fifth column in Table 6 Panel A shows that the marginal effect on *CentralSOE* and *NCentralSOE* are −3.541% and −0.693%, respectively. In economic terms, the P2P platforms affiliated with central SOEs have a weekly failure rate that is 3.541% less than that of non-SOE-affiliated P2P platforms, while the number for platforms with local SOEs is 0.693%. That is, P2P platforms affiliated with central SOEs have higher trading volumes, more investors, and higher survival probabilities than those affiliated with local SOEs, possibly because they have better creditability and they provide or are perceived to provide downside protections for the affiliated platforms.

6.2. Financial vs. Non-financial SOEs

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

$$Performance_{it} = + \times FinSOE_i + \times NFinSOE_i + \times Control_{it} + Province_i + Week_t + "_{it}; \qquad (9)$$

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

In Panel B of Table 6, the coefficients on *FinSOE* and *NFinSOE* for trading volume, number of investors, number of borrowers, and interest rates all carry the expected signs and almost all are statistically significant. Interestingly, the magnitudes of the coefficients are always larger for *FinSOE* than for *NFinSOE*. When we compare whether the differences between the financial and nonfinancial SOE coefficients are significant, we find that they are significant in most cases. We also estimate the survival probabilities for these

two types of SOE affiliations, with a similar specification as in Eq. (8). From the fifth column in Table 6 Panel B, the coefficient on *FinSOE* and *NFinSOE* are both negative, and the marginal effect is significantly larger for *FinSOE* than that for *NFinSOE*.

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

7. Conclusion

For the past few years between 2011 and 2018, P2P platforms have thrived in China and have provided an alternative, yet important, funding/investment channel. Unlike the P2P platforms in other countries, China's P2P platforms have many unique and interesting features, such as government involvement, guarantee on principals, and a large cross section of competing P2P platforms, all of which makes the P2P industry an interesting research topic.

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

Our study also has important implications for regulators. Clearly, governments play an important role in global financial markets. However, in terms of how governments influence financial development, the answers vary from one country to another. Our paper focuses on the Chinese P2P lending market, a significant component of the rising fintech industry. We provide evidence that government affiliation has positive correlations with performance measures in the peer-to-peer lending market during its expansion period. This finding might be useful for other emerging markets aiming to develop a fintech industry, in fields like robo-advising, insuretech, digital payment and digital wallet, etc. Government affiliations may help FinTech companies in their early times to attract customers, gain survival probabilities, and thus bolster financial innovation. However, it remains an open question what the optimal form of government involvement would be, when the fintech industry gradually matures.

Our paper focuses on the expansion period of the P2P industry. One might be aware that over 2019 and 2020, the P2P industry in China went through dramatic policy changes, and number of platforms quickly shrank to double digit. The dynamics between the platforms and the government during contraction period should be another important research question for future studies.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

Appendix A. Individual examples on defaults and bailouts

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

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

For the non-SOE affiliated platforms, we found an example of ``Ezubao''. This platform was founded in 2014, and they attracted capitals from approximately 900,000 investors, in the amount of approximately 50 billion Chinese Yuan (around $7.6 billion). The

platform was shut down in December 2015, because it was reported to operate as a *Ponzi scheme*. The platform's founders were then sued and imprisoned. However, the salvage value from the platform and the founders is far below the amount they borrowed from the investors, so most of the investors lost big in this platform.

One popular approach that many platforms take for risk control is to form internal reserve funds to cover potential defaults. The P2P platforms are not required to report any details on these reserve funds. However, from IPO filings or other filings of platforms, which went public, we are able to collect two examples. First, in the IPO filings[13] of Jiayin Group Inc., which owns a P2P platform called ``Niwodai'', Jiayin states that it runs an ``investor assurance program'' which protect investors investments. From 2016 to 2018 September, the total payouts, which are total amount of cash paid to investors upon borrower's default, amount to RMB 5.7 billion (US$0.8 billion). Second, from the SEC filing, a U.S. listed Chinese P2P lending company ``PPdai Group Inc.'' runs a ``quality assurance fund'' and ``investor reserve funds'', with payout amounting to RMB 3.03 billion (US$ 0.44 billion) from 2015 to 2017 according to its form-1 filing.[14]

Appendix B. Additional details on regulations

Before 2015, there is no specific regulation on platforms. In July 2015, the People's Bank of China, or the PBOC, together with nine other regulatory agencies, jointly issued ``The Guidelines on Promoting the Healthy Development of Internet Finance'', or ``The Guidelines''.[15] The Guidelines seek to promote development of Internet Finance, or FinTech, encourage financial innovation, and believe that FinTech has a positive impact on both traditional financial sector and the overall economy, especially for small-and-medium-sized firms' development. One field that the Guidelines encourage is online peer-to-peer lending. Additionally, the Guidelines formally introduced for the first time the regulatory framework and basic principles governing the P2P lending industry. The Guidelines define online peer-to-peer lending as direct lending between individuals through an online platform, which is under the supervision of the Chinese Banking and Regulatory Commission (CBRC) and governed by the PRC Contract Law, the General Principles of the Civil Law of the PRC, and related judicial interpretations promulgated by the Supreme People's Court. Pursuant to the Guidelines, a company that provides online peer-to-peer lending information intermediary services shall function solely as an information intermediary and provide information services rather than provide credit enhancement services or engage in illegal fund-raising for platform itself.

After 2015, as fraud and scandals appeared more frequently in the media and began to negatively affect investors (for example, Ezubao, which collapsed in December 2015), the CBRC took actions to standardize the industry by introducing a series of detailed measures. In August 2016, the CBRC and other four regulatory agencies issued ``The Interim Measures on Administration of Business Activities of Online Lending Information Intermediaries'', or ``The Interim Measures''.[16] The Interim Measures further define P2P lending platform as online lending information intermediary and prohibit P2P platforms from engaging in certain activities, including among others, (i) fundraising for the platforms themselves, (ii) holding investors' fund, including accepting, collecting or gathering funds of lenders directly or indirectly,[17] (iii) providing guarantee to investors as to the principals and returns of the investment, (iv) raising funds by issuing financial products as wealth management products, (v) mismatch between investor's expected timing of exit and the loan's maturity date, (vi) securitization, (vii) promoting its financing products on physical premises other than through the permitted electronic channels, such as telephones, mobile phones and Internet,[18] (viii) providing loans with its own capital, except as otherwise permitted by laws and regulations, (ix) equity crowd-funding, (x) deducting interest from loan principal, (xi) outsourcing key services such as customer information collection, screening, credit evaluation, (xii) facilitating loans without a designated purpose,[19] and (xiii) cheating.

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

To strengthen supervision on P2P lending platforms, in October, 2016, the CBRC, along with the Ministry of Industry and Information Technology and the State Administration for Industry and Commerce, issued the ``Guidelines on the Filing-based Administration of the Online Lending Information Intermediaries'', or ``The Administration Guidelines''.[20] The Administration Guidelines set out rules on the filing-based administrative regime of online lending information intermediaries that require online lending information intermediaries shall apply for value-added telecommunications business operation licenses with certificate of registration issued by the local financial regulatory authority. However, to our best of knowledge, at least until February 2019, the financial regulatory authorities are still in the process of making detailed implementation rules regarding the filing procedures and none of the online lending information intermediaries have been permitted to apply for such filing.

To prevent platforms from running away with investor' money, in February 2017, the CBRC issued ``The Guidelines on Online Lending Funds Custodian Business'', or ``The Custodian Guidelines''.[21] One of the guidelines is to require the platforms to set up

---

[13] https://www.nasdaq.com/markets/ipos/filing.ashx?filingid=13116225, accessed on March 14, 2019.

[14] https://www.sec.gov/Archives/edgar/data/1691445/000119312517309953/d285990df1.htm, accessed on March 14, 2019.

[15] Official site for the Guideline: http://www.gov.cn/xinwen/2015-07/18/content_2899360.htm, accessed on March 14, 2019.

[16] Official site for the Interim Measures: http://www.cbrc.gov.cn/govView_37D312933F1A4CECBC18F9A96293F450.html, accessed on March 14, 2019.

[17] This requirement leads to the introduction of the Custodian Guidelines below.

[18] This requirement aims at preventing platforms from acquiring investors offline.

[19] This requirement aims at preventing borrowers from borrowing money from P2P platform and then investing in stock market.

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

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

custody accounts with commercial banks to keep the funds from being controlled by platforms. Through the usage of custodian banks, the proceeds of investing and collecting will go through the custodian bank, which make it less likely for platforms running away with investor's money.

To make the industry more transparent, the CBRC further issued the ``Guidelines on Information Disclosure of Business Activities of Online Lending Information Intermediaries'', or ``The Disclosure Guidelines'', in August, 2017.[22] Pursuant to the Disclosure Guidelines, P2P lending platforms shall disclose certain required information on their websites in a fair, accurate, complete and timely manner.

To the extent that the relevant P2P lending platforms are not in full compliance with the Administration Guidelines, the Custodian Guidelines, and the Disclosure Guidelines upon Guidelines' introduction, they are required to make correction or rectification within a rectification FE period specified by the Guidelines. Over the years of 2019 and 2020, the rectification continues, and no new regulation guidelines are added. As of June 2020, 29 platforms remain with outstanding loans of around 100 billion RMB.

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

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

Panel A. Match SOE-Affiliated platforms with Non-SOE-Affiliated platforms by size (1:3)						
	(1)	(2)	(3)	(4)	(5)	
	Ln(Trading volume)	Ln(#Investors)	Ln(#Borrowers)	Interest rate (%)	Cox coefficient	Hazard ratio
SOE	0.842***	0.779***	0.259	−2.325***	−1.954***	[0.142]
	(5.479)	(3.275)	(1.260)	(−6.271)	(−7.523)	
Week FE	Y	Y	Y	Y		
Observations	35,651	35,651	35,651	35,651	520	
R-squared	0.135	0.086	0.130	0.244	0.038	
Panel B. Using monthly data						
	(1)	(2)	(3)	(4)	(5)	
	Ln(Trading volume)	Ln(#Investors)	Ln(#Borrowers)	Interest rate (%)	Cox coefficient	Hazard ratio
SOE	0.910***	0.827***	0.200	−2.360***	−2.055***	[0.128]
	(6.954)	(3.936)	(1.163)	(−7.637)	(−8.172)	
Ln(Size)	0.266***	0.367***	0.255***	−0.249***	−0.137***	
	(7.031)	(6.204)	(5.278)	(−2.765)	(−6.819)	
Ln(Age)	1.334***	1.848***	1.739***	0.816***		
	(9.993)	(9.689)	(9.047)	(2.942)		
Ln(Term)	0.955***	0.706**	2.095***	−1.935***		
	(5.310)	(2.192)	(7.002)	(−3.863)		
Province FE	Y	Y	Y	Y	Y	
Month FE	Y	Y	Y	Y		
Observations	40,908	40,908	40,908	40,908	4,210	
R-squared	0.280	0.172	0.247	0.281	0.0126	

Appendix D. Platform survival patterns and macroeconomic conditions

This table examines the platform survival patterns during different macroeconomic conditions. The estimation results are based on the long sample using the following probit model, with size, age, and province fixed effects controlled.

$$\Pr(Defunct_{it}) = (\ + \ \times SOE_i + \ \times SOE_i \times MacroCondition_t + \ \times MacroCondition_t + \ \times Control_{it} + Province_i + "_{it}):$$

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

SOE is a dummy variable with a value of one for platforms affiliated with SOEs and zero otherwise. *MacroCondition* is *LowGDP*, *LowIncome*, or *HighUnemployment*. *LowGDP* is a dummy variable with a value of one when the GDP growth rate is below the sample average and zero otherwise. *LowIncome* is a dummy variable with a value of one when the urban household income growth rate is below the sample average and zero otherwise. *HighUnemployment* is a dummy variable with a value of one when the registered unemployment rate is over the sample average and zero otherwise. *Defunct i*s equal to one for platforms ceasing to exist at time *t* and zero for surviving platforms. Standard errors are clustered at the platform level. T-statistics are reported in parentheses. *** indicates the coefficient is different from zero at the 1% level, ** at the 5% level, and * at the 10% level.

	(1)	(2)	(3)
	Probit (Defunct = 1)		
SOE	−0.653***	−0.653***	−0.804***
	(−8.746)	(−8.745)	(−8.653)
SOE × LowGDP	−0.690***		
	(−6.048)		
LowGDP	3.654***		
	(107.617)		
SOE × LowIncome		−0.717***	
		(−6.467)	
LowIncome		3.656***	
		(116.487)	
SOE × HighUnemployment			−0.760***
			(−4.975)
HighUnemployment			0.753***
			(−21.134)
Controls, Province FE	Y	Y	Y
Observations	397,617	397,617	397,617
R-squared	0.0347	0.0353	0.0537

Appendix E. The NIFA sample and platform profitability

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

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

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

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

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

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

Panel A. Summary statistics (N = 89)							
	Mean	Std. Dev.	P1	P25	Median	P75	P99
SOE	0.157	0.366	0	0	0	0	1
Size/Registered capital (million CNY)	76.519	55.279	10	31.579	53.125	100	200
Age (years)	2.991	1.373	0.419	2.222	2.589	3.405	7.8
Defunct	0	0	0	0	0	0	0
Panel B. Platform profitability and SOE affiliation							
	(1) Profit_POS		(2) ROA		(3) Earnings ratio		
SOE	0.087		−0.161		−0.254		
	(0.191)		(−1.511)		(−0.383)		
Ln(Size)	0.366**		0.081*		0.069		
	(2.007)		(1.990)		(0.268)		
Ln(Age)	−0.012		0.016		−0.202		
	(−0.026)		(0.153)		(−0.302)		
Province FE	Y		Y		Y		
Observations	89		89		89		
R-squared	0.076		0.144		0.045		

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

Appendix F. Additional results on fake SOE

To further understand whether the SOE affiliations affect investor behaviors as a perception on platform quality or a signal for real platform quality, we also compare the performances of platforms with fake SOE affiliations to those of platforms with (real) SOE affiliations. Empirically, for each fake-SOE-affiliated platform, we match it with three SOE-affiliated platforms with similar sizes, ages, and provinces at the beginning of the sample. Based on the matched sample, we estimate the following specification:

$$Performance_{it} = \ + \ \times RealSOE_i + Week_t + "_{it}:$$

Here we restrict the sample to the week before the revelation.

Real SOE Affiliation vs. Fake SOE Affiliation, Matched sample			
	(1) Ln(Trading volume)	(2) Ln(#Investors)	(3) Interest rate (%)
RealSOE	−0.037	−0.867	−1.540
	(−0.095)	(−1.287)	(−1.430)
Week FE	Y	Y	Y
Observations	4469	4469	4469
R-squared	0.310	0.274	0.564

In the first regression for trading volume, the coefficient on RealSOE is −0.037, with an insignificant t-statistic of −0.095. In the second regression for number of investors, the coefficient on RealSOE is −0.867, with an insignificant t-statistic of −1.287. That is to say, we do not find significant differences between performances of fake SOE platforms and real SOE platforms.

Further, we investigate whether platforms with real SOE affiliations offer a higher interest rate for investors than platforms with fake SOE affiliations. In the third regression, the coefficient on RealSOE is −1.540 with an insignificant t-statistic of −1.430, indicating that the interest rates offered by a real-SOE-affiliated platform on average are 1.540% lower than that by a fake-SOE-affiliated platform. Again, we do not find significant differences between interest rates offered by fake SOE platforms and real SOE platforms.

The figure below shows the performance for fake-SOE-affiliated platforms and matched non-SOE-affiliated platforms, from six weeks before the revelation of fake SOE affiliation to two weeks after the revelation. Panel A shows the results captured by the natural logarithm of trading volume and Panel B the natural logarithm of number of investors. The sample is constructed based on the matching procedure described in Section 5.1.
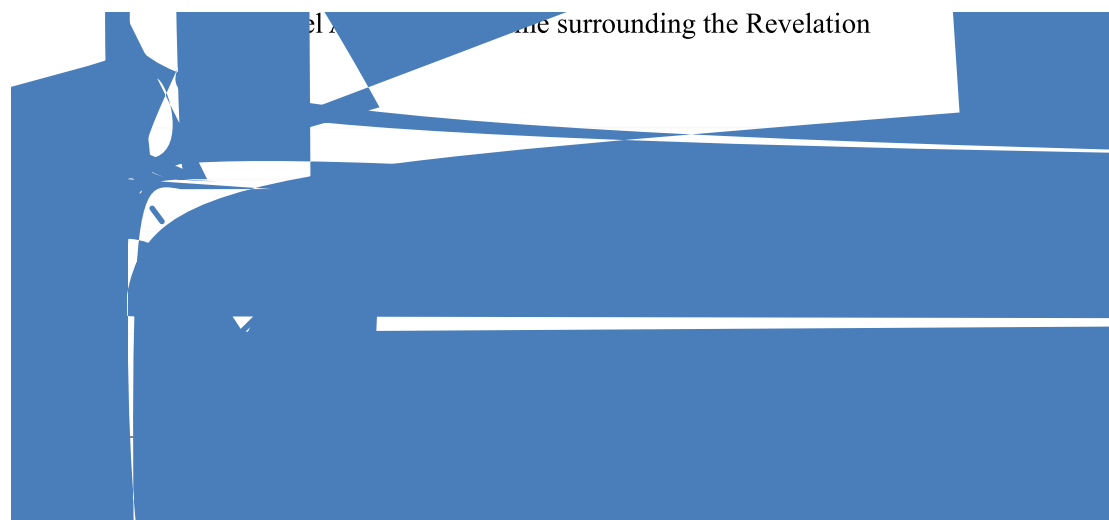
References

Acharya, V.V., Kulkarni, N., 2019. Government Guarantees and Bank Vulnerability During the Financial Crisis of 2007 09: Evidence from an Emerging Market. Working Paper, NYU Stern School of Business.

Ackermann, C., McEnally, R., Ravenscraft, D., 1999. The performance of hedge funds: risk, return, and incentives. J. Financ. 54, 833 874.

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

Bai, C., Lu, J., Tao, Z., 2006. The multitask theory of state enterprise reform: empirical evidence from China. Am. Econ. Rev. P & P. 96, 353 357.

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

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

Buchak, G., Matvos, G., Piskorski, T., Seru, A., 2018. Fintech, regulatory arbitrage, and the rise of shadow banks. J. Financ. Econ. 130, 453 483.

Carter, M., 1989. Financial innovation and financial fragility. J. Econ. Issues 23, 779 793.

Chemmanur, T.J., Loutskina, E., Tian, X., 2014. Corporate venture capital, value creation, and innovation. Rev. Financ. Stud. 27, 2434 2473.

Chen, Y., Démurger, S., Fournier, M., 2005. Earnings differentials and ownership structure in chinese enterprises. Econ. Dev. Cult. Change 53, 933 958.

Chen, M., Wu, Q., Yang, B., 2019. How valuable is fintech innovation? Rev. Financ. Stud. 32, 2062 2106.

DeFond, M.L., Wong, T.J., Li, S., 2000. The impact of improved auditor independence on audit market concentration in China. J. Account. Econ. 28, 269 305.

Duarte, J., Siegel, S., Young, L., 2012. Trust and credit: the role of appearance in peer-to-peer lending. Rev. Financ. Stud. 25, 2455 2484.

Fuster, A., Plosser, M.C., Schnabl, P., Vickery, J., 2019. The role of technology in mortgage lending. Rev. Financ. Stud. 32, 1854 1899.

Glaeser, E., Johnson, S., Shleifer, A., 2001. Coase versus the coasians. Q. J. Econ. 116, 853 899.

Heimer, R., 2016. Peer pressure: social interaction and the disposition effect. Rev. Financ. Stud. 29, 3177 3209.

Hertzberg, A., Liberman, A., Paravisini, D., 2018. Screening on loan terms: evidence from maturity choice in consumer credit. Rev. Financ. Stud. 31, 3532 3567.

Hildebrand, T., Puri, M., Rocholl, J., 2017. Adverse incentives in crowdfunding. Manag. Sci. 63, 587 608.

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

Iyer, R., Khwaja, A.I., Luttmer, E.F., Shue, K., 2015. Screening peers softly: inferring the quality of small borrowers. Manage. Sci. 62, 1554 1577.

Kiefer, N., 1988. Economic duration data and hazard functions. J. Econ. Lit. 26, 646 679.

Kornai, J., 1986. The soft budget constraint. Kyklos 39, 3 30.

Liao, L., Liu, B., Wang, H., 2014. China's secondary privatization: perspectives from the split-share structure reform. J. Financ. Econ. 113, 500 518.

Lin, M., Prabhala, N.R., Viswanathan, S., 2013. Judging borrowers by the company they keep: friendship networks and information asymmetry in online peer-to-peer lending. Manag. Sci. 59, 17 35.

Lu, D., Thangavelu, S.M., Hu, Q., 2005. Biased lending and non-performing loans in China's banking sector. J. Dev. Stud. 41, 1071 1091.

Pope, D., Sydnor, J., 2011. What's in a picture? evidence of discrimination from prosper.com. J. Hum. Resour. 46 (1), 53 92.

Rajan, R.G., 2006. Has finance made the world riskier? Eur. Financial Manage. 12, 499 533.

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

Seru, A., Shumway, T., Stoffman, N., 2010. Learning by trading. Rev. Financ. Stud. 23, 705 739.

Simon, C., 1989. The effect of the 1933 securities act on investor information and the performance of new issues. Amer. Econ. Rev. 79 (3), 295 318.

Song, Z., Storesletten, K., Zilibotti, F., 2011. Growing like China. Amer. Econ. Rev. 101, 196 233.

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

Tang, H., 2019. Peer-to-peer lenders versus banks: substitutes or complements? Rev. Financ. Stud. 32, 1900 1938.

Vallee, B., Zeng, Y., 2019. Marketplace lending: a new banking paradigm? Rev. Financ. Stud. 32, 1939 1982.

Wei, Z., Lin, M., 2017. Market mechanisms in online peer-to-peer lending. Manag. Sci. 63, 4236 4257.

Yin, C., 2016. The optimal size of hedge funds: conflict between investors and fund managers. J. Finance. 71 (4), 1857 1894.