Monitoring Fintech Firms:
Evidence from the Collapse of Peer-to-Peer Lending Platforms

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This Version: August 1st, 2023

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Abstract

In recent years, numerous Chinese peer-to-peer (P2P) lending platforms have collapsed, prompting us to investigate the regulation and monitoring of the fintech industry. Using a unique dataset of P2P lending platforms in China, we examine the effect of government monitoring on platform collapses. Exploiting platforms' locational proximity to regulatory offices as a proxy for government monitoring, we show that greater geographical distance results in a higher likelihood of platform collapse. Specifically, for every 10% increase in the driving distance from the platform to the local regulatory office, the likelihood of collapse increases by 10.2%. To establish causality, we conduct a difference-in-differences analysis that exploits two exogenous shocks: government office relocation and subway station openings. We further explore two underlying channels: the information channel through which greater regulatory distance reduces the likelihood of regulators' onsite visits and the resource constraint channel, through which greater regulatory distance significantly increases the local regulatory office's monitoring costs. Overall, this study highlights the importance of *onsite* regulatory monitoring to ensure the viability of *online* lending platforms.

Keyword: P2P lending; Platform collapse; Soft information; Monitoring; Regulatory distance
JEL code: G20, G23, G30

1. Introduction

Peer-to-peer (P2P) lending platforms provide innovative financing channels for individuals and institutions, because they allow borrowers and lenders to engage in credit transactions without traditional financial intermediaries (Wei & Lin 2017). Prior studies mainly focus on platforms' screening and monitoring of borrowers (Fuster *et al.* 2019; Vallée & Zeng 2019; Di Maggio & Yao 2021; Bartlett *et al.* 2022); scant research considers the monitoring and regulation of P2P lending platforms themselves. We fill this gap by exploiting the dynamics of the Chinese P2P lending market.

In the context of the Chinese fintech industry, regulation and monitoring are especially important given the exponential growth in the number of platforms and the scale of investment in the initial stage. As of 2019, the Chinese P2P lending market had attracted 50 million investors, and a total of 6,887 P2P lending platforms had ever been established in China.[1] Despite this rapid growth, recent years have seen waves of platform collapses, many of which have involved fraud.[2] The scale of platform collapses implies a potential lack of appropriate regulation, which prompts us to investigate the role of regulatory authorities in the practices and operations of fintech firms.

We examine the effect of government monitoring on P2P lending platform collapses from a unique perspective of *regulatory distance*, defined as the geographical distance between a P2P lending platform and the local regulatory office. Studies document that proximity facilitates information collection and reduces information asymmetry, especially for soft information (Coval & Moskowitz 2001; Malloy 2005; Kedia & Rajgopal 2011; Kubick *et al.* 2017). Given the complexity and opacity of P2P lending platforms' operations and the lack of existing rules for the fintech sector, we expect regulatory distance to play a crucial role in affecting information acquisition and supervisory monitoring.

It is unclear ex ante whether proximity to regulatory authorities could improve monitoring and promote prudent practices. On the one hand, Agarwal and Hauswald (2010) document that borrowers' proximity to lenders enables lenders to collect high quality soft information about borrowers and that distance erodes lenders' ability to collect proprietary intelligence. Lim *et al.*

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[1] Source: https://shuju.wdzj.com/industry-list.html

[2] Many fraudulent P2P lending platform operators lured investors with the promise of high returns, but instead they experienced huge losses, which led to widespread public grievance, evidenced by petitions and protests across China. For example, in 2016, a P2P lending platform Ezubo defrauded more than 900,000 people out of the equivalent of 60 billion yuan (about 8.5 billion US dollars) by promising returns as much as 10 times higher than the official deposit rate, making it the largest Ponzi scheme in Chinese history. Source: https://www.bloomberg.com/news/articles/2016-02-03/china-s-biggest-ponzi-scheme-shows-rot-in-internet-financing

(2017) show that geographical proximity to regulators improves the efficacy of monitoring and leads to better quality financial reporting by banks. On the other hand, proximate firms are better able to react strategically, as they have more and better information to predict local regulatory changes. Kubick *et al.* (2017) find that corporations avoid more tax when located closer to the IRS, as proximity provides them with an information advantage over the IRS.

We hypothesize that platforms located farther from the local regulatory office would have a higher collapse likelihood, for the following two main reasons. First, timely communication between regulators and P2P lending platforms via onsite visits are important means of information exchange, which facilitate monitoring and ensure platforms' prudent operations. When the regulatory distance increases, for regulators, the acquisition and transmission of soft information about the platform's operations will be less timely and accurate, potentially reducing the quality of the information collected and impeding regulatory scrutiny (Agarwal & Hauswald 2010; Kedia & Rajgopal 2011; Hollander & Verriest 2016; Kubick *et al.* 2017; Duchin *et al.* 2020). For P2P lending platforms, a shorter regulatory distance makes it more convenient for the platforms to follow the instructions and policies of local regulators. Proximity to local regulators makes it easier for platforms to be attuned to policy updates and to adjust their business scope in a timely manner to comply with rules and regulations, reducing the collapse likelihood.

Second, regulatory distance affects the cost of monitoring activities. The greater the regulatory distance, the higher transportation and communication related costs that the local regulatory authority incurs in the monitoring process, such as vehicles and staff transfer. Given the limited resources of local regulatory authorities, local regulators are more likely to visit and monitor nearby (as opposed to distant) P2P lending platforms, ensuring the prudent operations (Agarwal & Hauswald 2010; Lim *et al.* 2017; Nguyen & Nguyen 2017).

To test the hypothesis empirically, we collect Chinese P2P platforms' operation data from 2007 to 2019, consisting of 18,044 platform-year observations. The information on office locations of P2P lending platforms is obtained from WDZJ (www.wdzj.com), an online third-party P2P lending platform information provider. Our measure of regulatory distance is defined as either the driving distance or the driving time between the local regulatory office and the P2P lending platform's office, using geographic information from Baidu Maps (map.baidu.com).[3]

[3] Studies on the role of geographic distance in financial markets typically use the straight-line distance between two places (Malloy 2005; Landier *et al.* 2009; Tian 2011; Goetz *et al.* 2013; Wang & Xia 2014; Beck *et al.* 2018; Duchin *et al.* 2020; Lin *et al.* 2021). Such measures, however, have limitations; for example, there may be

We then use a logit model to test the effect of regulatory distance on the collapse rate of P2P lending platforms. We find a significantly positive relationship between regulatory distance and the collapse of P2P lending platforms, consistent with our hypothesis. Specifically, for every 1% increase in the driving distance between the local regulatory office and a P2P lending platform, the P2P platform's collapse likelihood increases by 1.01%; and after controlling for platform and city characteristics along with other fixed effects, for every 1% increase in driving time, the likelihood of collapse rises by 1.02%.

A potential concern is that the relationship between regulatory distance and the collapse of P2P lending platforms may not be causal, because these two variables may be endogenously determined by other latent variables, such as platform quality or management prudence. Specifically, platforms that intend to engage in scams or frauds may choose locations distant from financial regulators to avoid scrutiny. Hence, platforms farther from the local regulatory office may be more likely to engage in fraudulent activities and may not intend to follow government regulations. Consequently, these platforms are more likely to collapse than those with sound and regular practices.

To address these endogeneity concerns and establish causality, we employ a variety of identification strategies. First, we conduct a series of difference-in-difference (DID) analyses that exploit exogenous shocks. Our first DID test uses the variation in regulatory distance from a quasi-natural experiment: the relocation of a municipal government office, the Hangzhou government office, on October 1, 2016.[4] This relocation event exogenously changed the distance between the local regulatory office and all the active P2P lending platforms it supervised. In this setting, our treatment group includes the platforms established before the relocation whose distance to the local regulatory office increased after the relocation. Our control group includes all other platforms in other cities. The results show that the collapse rate of P2P lending platforms in the treatment group significantly increased after the relocation event, consistent with our baseline result that a greater regulatory distance leads to a higher collapse rate for P2P lending platforms.

Our second DID test uses the opening of new subway stations near the registered offices of P2P lending platforms as an exogenous shock. Levine *et al.* (2020) use travel time between a bank's headquarters and its branches to proxy for the costs of communicating soft information. They exploit shocks to these travel times –the introduction of new airline routes – to evaluate

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obstacles such as rivers or mountains between the two places that affect the actual travel time.

[4] The Hangzhou financial regulator, as a direct agency of the Hangzhou government, has the same office location as the Hangzhou government.

the impact of within-bank communication costs on small-business loans. In our setting, after the opening of a subway station near a P2P lending platform, transportation costs are reduced, and information exchange between the platform and local regulators is expected to improve. In addition, because traffic conditions near the P2P lending platform also improve because of the new subway station, the travelling difficulty and the cost of onsite supervision by the local regulatory authority substantially decrease, facilitating supervision and monitoring of the platform. Our treatment group includes P2P lending platforms within 1 kilometre of the nearest subway station that were in operation before that station opened. This setting ensures that the platforms in our treatment group experienced the effect of the subway opening. Our empirical results show that the opening of new subway stations significantly reduces the collapse rate of P2P lending platforms.

To further alleviate the endogeneity concern regarding distance, we use the instrumental variable (IV) approach, using the number of streets one needs to pass in order to drive to the P2P lending platform's office as an instrument variable. This instrument satisfies both validity requirements. It is strongly correlated with both driving distance and time from the local regulator's office to the P2P lending platform's office. However, it does not directly affect the collapse rate of P2P lending platforms. The results of our IV-approach analysis also show a positive effect of regulatory distance on the collapse of P2P lending platforms, supporting our baseline results.

We next examine potential underlying economic mechanisms through which regulatory distance might affect the collapse rate of P2P lending platforms. Two channels are proposed: the information exchange channel and the resource constraint channel. First, to test the information exchange channel, we manually collect data for local government leaders' visits to P2P lending platforms. We use the likelihood of local government leaders' visits to P2P lending platforms to measure the extent of information exchange between local regulators and P2P lending platforms. Our empirical results show that greater regulatory distance significantly reduces the likelihood of local government leaders' visits to P2P lending platforms. This finding suggests that information exchange is a potential mechanism through which regulatory distance affects the collapse of P2P lending platforms.

Second, we explore the supervision resource channel. Regulatory authorities need to deploy sufficient resources to supervise P2P lending platforms, ensuring they meet policy requirements and undertake prudent risk management. We expect greater resources deployed on supervision activities would have a moderating effect on the impact of regulatory distance on the collapse rate of P2P lending platforms. We use government financial supervision expenditures of the city where the P2P lending platform is located to measure the resources deployed on supervision activities. Our empirical results show that greater regulatory resources deployed by financial regulatory authorities on supervision could effectively attenuate the positive impact of distance on the likelihood of collapse. This result confirms supervisory resource constraints as a viable channel through which regulatory distance affects the collapse rate of P2P lending platforms.

In additional analyses, we examine the moderating effect of local regulators' supervisory discretion. Studies document that when regulators have greater discretion, they tend to choose not to enforce standards due to corruption or incompetence (Stigler 1971; Johnson *et al.* 1998). With greater discretionary powers, local regulators tend to pursue their private benefits rather than public goals (Weingast & Moran 1983). In the same vein, we exploit a policy change to the discretionary power of local regulators. The regulatory powers of China's local authorities over P2P lending platforms were clarified in 2016, reducing the regulatory discretion of local financial offices. After August 2016, responsibility for the supervision of P2P lending platforms clearly belonged to local financial authorities. We would expect local regulators to exert more efforts in monitoring the platforms regardless of locational proximity. As expected, we find that after the clarification of responsibilities, the effect of regulatory distance on the collapse of P2P lending platforms indeed became weaker.

Last, we further distinguish two main types of platform failures, namely fraud-related collapse versus benign exit, and examine the effect of regulatory distance on the collapse rate of each type. We find that increased regulatory distance results in a lower likelihood of benign exit and a higher likelihood of shutdowns related to fraudulent activities. These results are consistent with the rationale that greater regulatory distance is associated with less supervisory guidance, resulting in a greater likelihood of fraud-related collapses and lower likelihood of orderly benign close-downs.

This study makes the several important contributions to the literature. First, it adds on to the growing literature on fintech and, lending platforms in the sharing economy. Most studies in this area examine information asymmetry between borrowers and lenders (Herzenstein *et al.* 2011; Duarte *et al.* 2012; Michels 2012; Iyer *et al.* 2016), investment behaviour (Zhang & Liu 2012; Lin & Viswanathan 2016; Vallée & Zeng 2019; Franks *et al.* 2020; Liao *et al.* 2020), and expanded access to credit (Rigbi 2013; Tang 2019). These studies usually focus on risks at the individual borrower or lender level. Scant literature considers the monitoring and regulation of platforms themselves. Using multiple unique data sets from China's P2P lending market, this study investigates the effect of driving distance and time between the local regulatory office and a P2P lending platform on the platform's collapse likelihood. Given the waves of platform collapses in China, this study provides an understanding on this important issue from the perspective of regulatory distance.

Second, this study contributes to the literature on the effect of geographic distance between regulators and firms they supervise on financial regulation and monitoring. The geographic distance between a regulator and listed firms can significantly affect financial misconduct (Kedia & Rajgopal 2011; Parsons *et al.* 2018), tax avoidance (Kubick *et al.* 2017), and insider trading (Nguyen & Nguyen 2017). This study sheds important light on the regulation of P2P lending platforms and is among the first to document that an increase in regulatory distance increases the difficulty of information acquisition, increasing the collapse rate of P2P lending platforms.

Third, this study contributes to the strand of the literature on soft versus hard information in financial transactions and markets. As the disclosure requirement on financial statements to the public is relatively lax, the operations and risk management of P2P lending platforms is relatively opaque to other market participants, such as investors and regulators. Therefore, soft information becomes more important to market participants because hard information is difficult to access. We document that geographic distance plays an important role in the transmission and collection of soft information.

In the last decade, China's P2P online lending market has gone from exponential growth in the early 2010s to being phased out in 2020. To resolutely prevent and fend off systemic financial risks and make the financial sector better serve the real economy, Chinese officials decided to zero out all P2P lending platforms in November 2020. Although P2P lending platforms no longer play an active role in China's financial system, the boom-and-bust cycle undergone by the Chinese P2P industry offers important lessons for the future supervision of the fintech industry.

The remainder of this paper is organised as follows. Section 2 describes the institutional background and develops the research hypothesis, and Section 3 details the variables and sample. Section 4 presents the empirical results. Section 5 explores plausible underlying mechanisms. Section 6 reports the results of additional analyses and robustness tests. Section 7 concludes the paper.

2. Institutional background and hypothesis development

2.1 The Chinese P2P online lending market

In the last decade, the transaction volume of China's P2P lending market has grown exponentially. In 2009, it was only 0.1 billion yuan (about 14 million US dollars), but in 2017, it reached a peak of 2,804 billion yuan (about 400 billion US dollars). It has become the world's largest P2P lending market. According to the WDZJ website, there were fewer than 30 P2P lending platforms in China before 2010. By December 2019, China had 6,887 P2P lending platforms.[5]

Despite this remarkable growth, it appears that regulation and monitoring have been inadequate. Waves of collapses have hit China's P2P lending industry. Panel A of Figure 1 illustrates the collapse rate of P2P lending platforms in the industry's early and later development periods. Before 2012, only 16 P2P lending platforms in China had collapsed. In stark contrast, 1,717 P2P online lending platforms collapsed in 2016 alone. Panel B of Figure 1 shows that the number of platforms peaked at 3,798 in the fourth quarter of 2015. By October 2019, of the 6,887 P2P lending platforms that had been established in China, 5,285 had collapsed, leaving only 1,602 in operation.[6]

[------ Insert Figure 1 here -----]

Figure 2 presents a heat map of the platform collapse rate for each Chinese province, in which darker blue indicates a higher collapse rate and darker green indicates the opposite. The illustration shows that provinces with strong private lending demand, such as Shandong and Zhejiang, have higher collapse rates.[7]

[------ Insert Figure 2 here -----]

There are several reasons for the collapse of Chinese P2P lending platforms. First, most Chinese P2P lending platforms provide lenders with principal guarantees, to offer more assurance and boost lenders' confidence, because China's credit system has not yet fully developed. As of 2014, only one third of adults in China had a credit score, whereas the ratio was much higher, at 89% in the United States.[8] Without a well-developed social credit system, investors shun P2P loans because of loss and default concerns. Therefore, most Chinese P2P lending platforms provide investors with principal guarantees, in which the loan default risk

5 https://shuju.wdzj.com/industry-list.html
6 The numbers are from Table 2, Panel A.
7 Note that certain provinces, such as Gansu and Hainan, have abnormally high platform collapse rates because they have fewer P2P lending platforms.
8 https://www.economist.com/news/finance-and-economics/21710292-chinas-consumer-credit-rating-culture-evolving-fastand-unconventionally-just

that should be borne by lenders is instead borne by the platforms.

Second, P2P lending platforms lack prudent underwriting procedures and overestimate their ability to differentiate between good and bad borrowers. Even with artificial intelligence and big data technology (Goldstein *et al.* 2019; Berg *et al.* 2020), many Chinese P2P lending platforms do not do enough in terms of risk management. As a result, many low-quality borrowers have been inappropriately granted loans. In the event of large-scale borrower defaults, the losses would be more than the platforms could absorb, substantially increasing their collapse risk.

Third, China's financial regulations did not keep up with the rapid growth of the P2P lending industry. For instance, China's first P2P lending platform PaiPaiDai was established in 2007, but China's financial regulatory authorities only introduced regulations for the P2P lending industry in 2016. By then, China's P2P lending market had reached 2,063 billion yuan (about 294 billion US dollars). The low barriers to entry and the lack of regulation resulted in the so-called 'barbaric growth' phase of China's P2P lending market before 2016, which included an influx of platforms that did not meet the regulatory standards that were later introduced.

Fourth, many of the P2P lending platforms had severe moral hazard issues. Some used their P2P lending platforms as disguise to run unscrupulous Ponzi schemes. Some high-profile fraud cases grabbed headlines, such as the P2P lending platform Ezubo that scammed investors out of nearly 60 billion yuan (about 8.5 billion US dollars) through fake investment projects from July 2014 to February 2016.

2.2 Supervision of P2P lending by local regulatory offices

In August 2016, the China Banking Regulatory Commission (CBRC) promulgated the Interim Measures for the Administration of the Business Activities of Online Lending Information Intermediary Institutions, also called the basic law of the P2P lending industry.

Figure IA 1 shows the regulatory policy timetable. In December 2018, the release of "Opinions on Doing a Good Job in the Classification and Disposal of Online Lending Institutions and Risk Prevention" clarified that the focus of China's financial regulatory authorities is to clamp down on P2P lending platforms in an orderly manner. As shown in Figure 3, from October 2019 to June 2020, 16 Chinese provinces announced bans on P2P lending platforms in their provinces.

[------ Insert Figure 3 here -----]

Compared with central-level authorities, local regulators are more familiar with market activities in their jurisdictions (Allen *et al.* 2005). Local regulators also have better access and pay more attention to local market information than do central-level regulators. They can also respond faster to local regulatory issues, especially in terms of law enforcement, because local governments can monitor and supervise the market more effectively.

Different from the dual supervision system of federal and state governments in some countries, such as the United States (Agarwal *et al.* 2014), China's financial supervision system is vertically managed by branches of the central government in various provinces and municipalities.[9] However, with the development of innovative banking technologies and the rapid expansion of the fintech industry, institutions that cannot be effectively supervised by China's vertical central agencies have gradually emerged. Therefore, local governments have set up special financial supervision departments to coordinate fraud prevention and handle local financial risks. Figure IA 2 shows that in 2011, 30 provinces/municipalities had such offices. The establishment of the Shanghai financial office in 2002 is generally considered the starting point of the growth of local regulatory offices. In the ten years after it was established, most provinces and municipalities established a local regulatory office.

Provincial and municipal offices differ in their specific regulatory objectives. Provincial offices enact the opinions of the central financial supervisory authority. They focus on the overall situation in the province, overseeing the general direction of the province's financial supervision and guiding the local offices in subordinate prefectures. In consideration of the differences in the development of financial markets in different regions of a province, the provincial office formulates and implements the financial supervision regulations and policies of the province. The supervisory objectives of municipal financial offices are more specific and microscopic. They focus on blocking the transmission of regional financial risks, preventing regional financial risks and creating a strong local financial market. Indeed, municipal offices were the first to deal with financial risks such as the supervision of illegal fund-raising and private lending within the jurisdiction.

The emergence of P2P lending has created a new financing channel for both borrowers and investors, but these new institutions often operate on the edges of the existing financial

[9] Figures IA 3-1 and IA 3-2 show the supervisory responsibilities of the Beijing and Shanghai municipal financial affairs offices. Their two main responsibilities are (1) implementing national, provincial and municipal rules and regulations and (2) preventing and combating financial fraud, illegal fund-raising and other illegal activities. Figure IA 3-3 shows the 2018 performance appraisal targets of the Hangzhou financial office. It shows that 'preventing and handling financial risks' is the key goal of the Hangzhou financial office.

regulatory system. They are likely to infringe on the rights and interests of financial consumers in the absence of supervision, and their large scale of collapse pose challenges for local economies and even social stability. In terms of the supervision of P2P lending platforms, local regulators are more familiar with the market activities in their jurisdictions, so they can formulate and implement more targeted supervisory policies.[10] Considering the special role that local offices play in supervising P2P lending platforms, this study focuses on the effect of the geographic distance between municipal offices and P2P lending platforms on the collapse of P2P lending platforms.

2.3 Hypothesis development

Scant literature examines the risks and monitoring of P2P lending platforms, mainly because of the limited data availability. Given the scale of development of Chinese P2P lending platforms, most studies focus on China's P2P online lending market. Jiang *et al.* (2019) find that P2P lending platforms with state-owned enterprise affiliations have higher trading volumes, attract more investors, and offer lower interest rates. Li *et al.* (2019) study weekly trading data from 154 Chinese P2P lending platforms and find that venture capitals play a certification role and mitigate the information asymmetry between start-ups and their customers. Few studies explore the regulation of the fintech industry.

Several recent studies examine the effect of geographic distance on lending activities such as bank credit and the behaviour of individual investors (Petersen & Rajan 2002; Agarwal & Hauswald 2010; Hollander & Verriest 2016; Huang *et al.* 2017; Parsons *et al.* 2018; Duchin *et al.* 2020; Sialm *et al.* 2020). These studies document that the importance of geographic distance in economic transactions mainly concerns two factors: information acquisition and transaction costs. Geographic distance can affect the ability of market participants to collect and screen information. In a market with asymmetric information, soft information is particularly important, and those closer to the market are better able to perceive and interpret it. Given that soft information is difficult to standardise, communication between market participants is bound to be greatly limited by geographic distance. In addition, the cost of information collection and transmission increases significantly with the distance between two parties.

Because P2P lending platforms are profit-seeking entities subject to the conflicts of interest in the classic principal agent problem (Fama 1980; La Porta *et al.* 2000), their operations and

[10] Figures IA 4-1 and IA 4-2 illustrate two ways the Guangzhou financial office monitors the P2P lending market: onsite inspection and risk warnings.

management should be monitored and regulated in ways like those of financial companies and traditional banks. To fill a gap in literature, we focus on the role of government monitoring in the collapse of P2P lending platforms. Specifically, we measure government monitoring using the physical distance between a P2P lending platform and the local regulatory office.

Unlike listed firms, most fintech firms are start-ups and are not required to frequently disclose financial statements or operational details to the public. The business processes of such fintech firms are opaque to the public (Buchak *et al.* 2018). Local regulators can more easily collect soft information about nearby P2P lending platforms. Therefore, they can formulate targeted plans to improve non-compliant aspects of the business and reduce its collapse risk. If a local regulatory office and a P2P lending platform are far apart, it affects the timeliness of the transmission of soft information about the platform's operations, which may mislead local regulators.

From the platform's perspective, the farther the local regulatory office, the more difficult it is for the P2P lending platform to be fully aware of and understand the requirements of the local regulatory authority, so the business can ensure it operates appropriately. In contrast, the closer a P2P lending platform is to the local regulatory office, the more likely it is to formulate and adjust its operations in a timely manner according to the requirements of local regulators, increasing its likelihood of survival.

The geographic distance between a P2P lending platform and local regulatory office can also affect regulatory enforcement costs. Kedia and Rajgopal (2011) find that firms located closer to the SEC and in areas with greater past SEC enforcement activity, both proxies for firms' information about SEC enforcement, are less likely to issue financial restatements. Consistent with the resource-constrained SEC view, the SEC is more likely to investigate firms closer to its offices. Nguyen and Nguyen (2017) examine the effect of geographic distance on the SEC's enforcement activities related to insider trading. They find that the SEC is more likely to investigate companies closer to its offices. Regulation involves costs, and regulators face resource constraints, so regulatory distance is an important factor affecting regulation. The greater the regulatory distance, the more resources, such as vehicles, time and personnel, required for financial regulatory work.

As the local financial regulatory offices are subject to local government budgets and human resources are limited, local financial regulatory authorities cannot invest all their human and material resources in the supervision of the P2P lending industry. Under such constraints, local regulators are more likely to engage in the supervision of nearby P2P lending platforms, and these platforms are more likely to be subject to onsite supervision and investigation. Therefore, P2P lending platforms closer to the local regulatory office will be more self-disciplined and more likely to survive. In contrast, P2P lending platforms farther from their local regulatory office face a relatively loose regulatory environment. In turn, lax monitoring may increase the collapse rate of such P2P lending platforms.

According to this discussion, our hypothesis is as follows:

Hypothesis 1: Greater distance between a P2P lending platform and its local regulatory office is associated with a greater risk of collapse.

3. Variable construction and sample description

3.1 Variable construction

3.1.1 The collapse of P2P lending platforms

We collect information on the performance of P2P lending platforms, including office location and whether a platform has collapsed, from WDZJ and CSMAR and through manual collection.[11] We obtain platform performance data from CSMAR and cross validate it with the data from WDZJ to mitigate errors across the data providers.

Note that neither WDZJ nor CSMAR reports detailed reasons for the collapse of P2P lending platforms in their database; they only show whether a platform collapsed during a specific period. To understand whether a collapse of platform is involved in fraud or is a benign exit, we conduct manual Internet searches using the Baidu search engine to ascertain the nature of each platform's collapse.

Our main dependent variable is an indicator variable denoting whether a P2P lending platform collapsed at a specific time point. In the context of China's P2P industry, collapse is similar to but different from bankruptcy. In this study, we define a P2P lending platform's collapse as it terminating its P2P lending business (legal or illegal). The dependent variable *Collapse* equals one if a P2P lending platform had closed down during the year and zero otherwise.

3.1.2 Regulatory distance

We obtain the longitude and latitude of local regulatory offices and P2P lending platforms from Baidu Maps (map.baidu.com). Baidu Maps is a main data source for geographic

[11] Established in 2011, WDZJ (www.wdzj.com, directly translated as 'Home to P2P lending platforms') is China's first third-party consulting website for the P2P online lending industry. This website is currently the largest and most influential third-party P2P lending platform online information provider in the Chinese P2P lending industry.

information in mainland China with approximately 280 million active users monthly. We further collect the information on both driving distance and time between the two locations and the straight-line distances between the platforms and the headquarters of the top four Chinese commercial banks (Industrial and Commercial Bank of China, Agricultural Bank of China, China Construction Bank, and Bank of China) in the same city as the platforms.

We use the driving distance and time from the local regulatory office to a platform's office to measure supervision distance. Studies generally use the straight-line distance between a regulatory agency and regulated institution to measure regulatory distance. However, cities differ greatly in terms of size and area. For example, the straight-line distance between two places in Chongqing may be short; however, given its mountainous landscape, the travel distance can be much longer. Hence, we use the driving distance measure *(DriveDistance*) and the driving time measure (*DriveTime*) from Baidu Maps as our independent variables.

Figure IA 5 provides an example of the regulatory distance calculation. The optimal route between the Guangzhou financial office and the P2P lending platform PPMONEY is 7.6 kilometres with a driving time of 13 minutes, so *DriveDistance* (in km) and *DriveTime* (in minutes) are 7.6 and 13, respectively. We use the logarithm form of the variables (*DriveDistance* and *DriveTime*) in our empirical analysis.

3.1.3 Control variables

In addition to regulatory distance, we include two sets of control variables in the regression. The first set includes platform-level characteristics. *DistanceBank* measures the natural logarithm of the average distance between the headquarters of the four major banks and a P2P lending platform. Proximity to the four major banks indicates that the platform is located in the financial centre of a city and may have a better reputation and more industry connections. *RegCapital*, the natural logarithm of the total capital registered by the P2P lending platform with the registration management agency, represents the capital contributions all parties to the joint venture have paid or promised to pay, in millions of RMB.

Collateral is a dummy variable that equals one when the P2P lending platform provides mortgage loan services and zero otherwise. *CapitalDeposit* is a dummy variable that equals one when investors' funds are required to be placed with a third-party financial institution and zero otherwise. A capital depository requirement may potentially prevent platform fraud and the withdrawal of funds to a certain extent. *RiskDeposit* is a dummy variable that equals one when the P2P lending platform has a risk deposit at a third-party financial institution and zero otherwise. When a loan is overdue or defaults, the platform uses this fund to repay investors in accordance with the platform's terms.

P2P lending platforms operate in different regions of China, and a city's level of economic and financial development can affect the participation in and demand for P2P lending in that city. Therefore, the second set of control variables includes city-level characteristics. Specifically, we control for GDP per capita (*GDP/PC*), the ratio of deposits to GDP (*Deposit/GDP*), and the ratio of loan balances to GDP (*Loan/GDP*) of the city where a P2P lending office is located that year. In addition, given that P2P lending activities are largely conducted via the Internet, we also control the number of mobile phones per capita (*MobilePhone/PC*). We obtain data for the city-level characteristics from Chinese Research Data Services (CNRDS). See Appendix 1 for detailed definitions of all the variables used in this study.

3.2 Sample and summary statistics

Our initial sample consists of 6,889 P2P lending platforms in China from 2007 to October 2019.[12] We then apply the following data filters to the initial sample. First, we exclude P2P lending platforms with missing information for office address, as we cannot calculate the regulatory distance. Second, we exclude P2P lending platforms with missing values for the control variables. Last, we exclude P2P lending platforms of which registered addresses and office addresses are inconsistent.[13] After this data screening, the final sample comprises 18,044 platform-year observations for 5,984 P2P lending platforms from 2007 to 2019, of which 4,802 P2P lending platforms have collapsed.

Table 1 presents the summary statistics of the key variables used in this study. The mean of *Collapse* is 0.266, implying that 26.6% of platforms collapsed each year between 2007 and 2019. The average value of *DriveDistance* is 17.883, indicating that the average driving distance between the local regulatory office and a P2P lending platform's office is 17 kilometres. The average of *DriveTime* is 24.031, indicating the average driving time between the local regulatory office and a P2P lending platform's office is 24 minutes. The average value of *DistanceBank* is 2.046, indicating that the average distance between the headquarters of the

[12] In 2007, the first P2P lending platform in China PaiPaiDai was established, and the P2P online lending industry started to grow. By October 2019, many P2P lending platforms had collapsed because of provincial administrative interventions and other reasons.

[13] If a P2P lending platform operates somewhere other than its registered address, its regulatory authority may be misidentified. Hence, we only keep the P2P lending platforms with registered and office addresses in the same city.

four major banks and a P2P lending platform's office is $e^{2.046} = 7.7$ kilometres. This shows that P2P lending platforms tend to be located near city financial centres.

[------ Insert Table 1 here -----]

Panel A of Table 2 shows the number of newly established and collapsed P2P lending platforms in China from 2007 to October 2019. This number peaked in 2015, with 2,652 newly established P2P lending platforms. The most collapses occurred in 2016, when 1,717 P2P lending platforms collapsed. As of October 2019, the overall collapse rate of P2P online lending platforms in China was 76.74%.

Panel B of Table 2 shows the provincial distribution of P2P lending platforms and the types of collapses. It shows that Beijing, Guangdong, and Shanghai are the top three P2P lending hubs in China, whereas Guangdong, Zhejiang, and Shanghai have the most fraud-related platform collapses. This distribution of collapsed platforms may be related to local economic development and strong demand for investment and financing.

[------ Insert Table 2 here -----]

4. Main results

4.1 Baseline analysis

To examine the effect of regulatory distance on the likelihood of platform collapse, we estimate the following logit regression model:

$$Collapse_{i,t} = \beta_0 + \beta_1 Distance_i + \beta_2 Control_{i,t} + Prov_i + Year_i + \varepsilon_{i,t}, \tag{1}$$

where $Collapse_{i,t}$ denotes whether P2P lending platform *i* collapsed in year *t*. It is a dummy variable that equals one if P2P lending platform *i* collapsed in year *t* and zero otherwise. $Distance_i$ denotes regulatory distance, measured using driving distance (*DriveDistance*) and driving time (*DriveTime*) between the local regulatory office and P2P lending platform *i*. We also control for platform-level and aggregate city-level characteristics. We further include provincial ($Prov_i$) and year ($Year_i$) fixed effects in the regression. $\varepsilon_{i,t}$ is the error term.

Table 3 reports the logit estimation results. In Columns (1) and (3), we regress *Collapse* on the regulatory distance variables. The results show that the coefficients on *DriveDistance* and *DriveTime* are positive and significant at the 1% level. In Columns (2) and (4), we add platform-level and city-level controls and province and year fixed effects, we find that the coefficients on *DriveDistance* and *DriveTime* remain positive and significant at the 1% level.

The marginal effect corresponding to *DriveDistance* in Column (2) is 0.011, that is, for every 1% increase in the driving distance between the local regulatory office and a P2P lending platform, the probability of the P2P lending platform collapsing increases by $e^{0.011}\times1\% = 1.011\%$, all else equal. The marginal effect of *DriveTime* in Column (4) is 0.016, which means that for every 1% increase in the driving time between the local regulatory office and a P2P lending platform, the platform's likelihood of collapse increases by 1.016% ($e^{0.016}\times1\%$), all else equal.

[------ Insert Table 3 here -----]

Overall, our results show a significant positive relationship between either the driving distance or the driving time from the local regulatory office to a P2P lending platform's office and the likelihood of the P2P lending platform's collapse. This finding that regulatory distance increases the likelihood of platform collapse has profound economic significance, implying better regulation could significantly reduce collapse risk.

4.2 Endogeneity tests using an event: the relocation of the Hangzhou government office

4.2.1 DID test results

Our results thus far suggest a positive relationship between regulatory distance and the collapse of P2P lending platforms. Given that the location of P2P lending platforms is non-random, there is a potential endogeneity concern that P2P lending platforms with sound management may locate closer to their local regulatory office to facilitate information acquisition and stay attuned to government policies. Conversely, platforms that locate far from their local regulatory office may intend to dodge regulatory scrutiny so their fraudulent activities are less noticeable in a weak regulatory environment. Consequently, these platforms tend to have a greater risk of collapse.

To address this self-selection problem, we use a DID strategy following Duchin *et al.* (2020), Ehrlich and Seidel (2018), and Mulalic *et al.* (2014). Duchin *et al.* (2020) examine the effect of the distance between government and enterprises on enterprise performance, using the relocation of 23 city governments as exogenous shocks to solve the self-selection concern. In the same vein, our treatment group consists of platforms located in cities that experienced government office relocations during our sample period.

Specifically, we use the relocation of a municipal government office, the Hangzhou government office, as a quasi-natural experiment.[14] Hangzhou is the capital city of Zhejiang

[14] Although the reasons for government office relocation are generally not publicly announced, it is reasonable to assume, based on the map in Figure IA5, that the relocation of the Hangzhou government office in 2016 was mainly for environmental protection purposes. Hence, we believe it is reasonable to consider it as an exogenous shock to P2P lending platforms.

province in China. The Hangzhou government office relocated on 1 October 2016 from No. 318 Huancheng North Road, Gongshu District, to No. 18 Jiefang East Road, Jianggan District. The geographic locations are illustrated in Figure IA 6. The Hangzhou municipal financial service office, a direct agency of the Hangzhou government, is located at the same address as the Hangzhou government. Figure IA 7 shows that the linear distance between the new and the old government offices is 6.1 kilometres. We also note that Zhejiang has 2,051 platform-year observations, and Hangzhou accounts for half of them, with 1,137 platform-year observations in Table 1.

We examine the effect of the Hangzhou government relocation on the collapse of P2P lending platforms by performing a standard DID test using the following regression:

$$Collapse_{i,t} = \beta_0 + \beta_1 Treat_i \times Post_t + \beta_2 Treat_i + \beta_3 Control_{i,t} + Prov_i + Year_i + \varepsilon_{i,t}, \quad (2)$$

where i indexes the P2P lending platform, and t indexes the year. $Collapse_{i,t}$ denotes whether P2P lending platform i is collapsed in year t. $Treat_i$ is a dummy variable that equals one if a P2P lending platform has been established before the relocation and has a longer straight-line distance to the local regulatory office after the relocation and zero otherwise.[15] The control group includes P2P lending platforms in Hangzhou that do not face a longer distance after government relocation and those that are not located in Hangzhou. $Post_t$ is a dummy variable that equals one for the 2017-2019 post-relocation period and zero otherwise. We control for other potential variables that may affect platform collapse, including platform- and city-level characteristics. We also include provincial ($Prov_i$) and year ($Year_i$) fixed effects in the regression.

The coefficient of interest is the coefficient on the interaction term *Treat*×*Post*, which captures the change in the collapse rate of the treatment group before and after the relocation compared with the control group. If greater regulatory distance increases the collapse rate of P2P lending platforms, after the relocation increased the regulatory distance, the probability of collapse should increase. Therefore, we expect the coefficient on *Treat*×*Post* to be positive and statistically significant.

[------ Insert Table 4 Panel A here -----]

Table 4 reports the results of the multivariate DID analysis. The treatment group includes the P2P lending platforms that are farther from the Hangzhou government office after its relocation, as measured by straight-line distance. To further address the endogeneity concern

[15] Figure IA 8 in the Internet Appendix provides an example.

that the platforms that experienced the relocation event differ from those that did not, we use the propensity score matching (PSM) method with the nearest neighbour algorithm to match each treatment platform with four platforms in the control group. The 1:4 matching ratio is to ensure that the platform characteristics and other covariates of the treatment and control groups are reasonably similar.

In Column (1), we use the full sample for the DID regression analysis, and we find that the coefficient on the interaction term (*Treat×Post*) is positive and statistically significant, indicating that greater regulatory distance resulting from exogenous relocation events increases the collapse rate of P2P lending platforms. We repeat the DID regression using the PSM sample in Column (2) based on a [-3, +3] years window around the relocation event. We find that the coefficient on *Treat×Post* is still positive and statistically significant at the 1% level, consistent with our baseline result that greater regulatory distance is associated with a higher collapse rate.

4.2.2 Parallel trend test

As the DID design requires that the treatment and control groups have parallel trends before the event, we examine their trends before the relocation of the Hangzhou government office to ensure the validity of our results. Specifically, we follow Bertrand and Mullainathan (2003), Atanassov (2013), Masulis and Zhang (2019), and Skrastins and Vig (2019), and examine the dynamics of the collapse rate of P2P lending platforms before and after the relocation event by estimating the following equation:

$$Collapse_{i,t} = \beta_0 + \beta_1 Treat_i \times Before3yr_{i,t}^{-3} + \beta_2 Treat_i \times Before1yr_{i,t}^{-2} + \beta_3 Treat_i \times Before1yr_{i,t}^{-1} + \beta_4 Treat_i \times After1yr_{i,t}^{1} + \beta_5 Treat_i \times After2yr_{i,t}^{2} + \beta_6 Treat_i \times After3yr_{i,t}^{3} + \beta_7 Control_{i,t} + Prov_i + Year_i + \varepsilon_{i,t}, \quad (3)$$

where $Before2yr_{i,t}^{-3}$ ($Before1yr_{i,t}^{-2}/Before1yr_{i,t}^{-1}$) is a dummy variable indicating a platform-year observation is three years (two years/one year) before the relocation event. $After1yr_{i,t}^{1}$ ($After2yr_{i,t}^{2}/After3yr_{i,t}^{3}$) is a dummy variable indicating an observation is one year (two years/three years) after the relocation event. All other variables are the same as in the baseline DID regression.

[------ Insert Table 4 Panel B here -----]

Panel B in Table 4 reports the results of our dynamic DID analysis where the coefficients of interest are β_1, β_2 and β_3 for the pre-relocation period. We find that the estimated β_1, β_2 and β_3 are statistically insignificant in all of the regressions, indicating that the parallel trend assumption underlying our DID analysis holds. The absence of any difference in the premove trends implies that the positive effect of increased regulatory distance on the collapse rate of P2P lending platforms is not due to the Hangzhou government simply responding to the demand for supervision of P2P lending platforms.

For the first year after the government relocation, β_4 is not significant, implying that greater regulatory distance does not increase the collapse rate of P2P lending platforms. However, the coefficients β_5 and β_6 are significantly positive, indicating that starting in the second year after the government relocation, the collapse rate for platforms farther from the government's new address increased significantly.

In Figure IA 9 of the Internet Appendix, we illustrate the time trend of the platform collapse rate with respect to the relocation event (Gropp *et al.* 2019). It shows that before the relocation, the collapse rates for the treatment and control groups did not vary significantly. However, the collapse rate for the treatment group increased significantly after the relocation, especially in the second year.

4.2.3 Covariate balance test

To ensure the platforms in the treatment and control groups are indeed similar in their observable characteristics, we conduct a balance test on the differences in the mean values of the platform characteristics and city-level control variables between the two groups. The results are shown in Table IA 1. Panel A shows that most of the characteristics do not differ significantly between the treatment and control groups after PSM, except for three control variables at the city level. Panel B shows that before the relocation of the government office, majority of the city-level control variables at the city level do not differ significantly between the treatment and control groups, except only two variables. These results support the underlying assumption of the DID analysis, that the change in distance after the relocation is uncorrelated with other P2P lending platforms attributes that may affect their collapse, hence addressing the potential endogeneity concern.

4.2.4 Placebo tests of the treatment effect

To ensure the observed effect of the relocation event is driven by the treatment, not confounding factors, we conduct placebo tests for robustness. Specifically, we adopt two placebo tests. First, we use the P2P lending platforms whose distance to the Hangzhou government office decreased with the relocation as a pseudo-treatment group. These platforms should have a lower collapse rate after the policy was strengthened in 2016, so we use this pseudo-treatment group and conduct a similar DID regression analysis. The results are reported in Table IA 2 in the Internet Appendix. We find that the DID estimators are statistically insignificant, implying that the policy event does not significantly affect the P2P lending platforms closer to the government office after the relocation.

Second, we conduct simulations that artificially assign the P2P lending platforms in our sample to the treatment group (Bradley *et al.* 2017; Pool *et al.* 2019; Kong *et al.* 2020). Specifically, for each simulation, we randomly choose a non-Hangzhou city and use the P2P lending platforms in that city as the pseudo-treatment group. As the government relocation occurred in 2016, we conduct DID regressions using the same specification as in Column (1) of Panel A in Table 4 with this pseudo-treatment group and repeat this process 5,000 times.

We summarise the distribution of the coefficients and *p*-values of $Treat \times Post$ from the DID regressions in Table IA 3 in the Internet Appendix, in which the statistics for the mean, 5th percentile, 25th percentile, median, 75th percentile and 95th percentile is reported. We find that the mean value of the coefficient distribution of the interaction term is positive but insignificant in this placebo test. Figure IA 10 in the Internet Appendix shows the probability density function of the coefficients on the interaction term from the 5,000 estimates. The mean value of the coefficient distribution of the interaction term is close to zero in this placebo test, which shows that our results are not driven by confounding factors but specifically by the relocation event, validating our main results.

4.3 Endogeneity tests using an exogenous event: subway station openings

In this section, we use sudden changes in the transportation costs between the local regulatory office and P2P lending platforms as an exogenous shock to identify the causal relationship between regulatory distance and the collapse of P2P lending platforms. This approach is widely used in the literature, such as Anderson (2014) and Gu *et al.* (2020). Specifically, using strikes by Los Angeles County Metropolitan Transportation Authority workers in 2003 to investigate the effect of public transportation services on road congestion, Anderson (2014) finds that strikes increase ground transportation delays by 47% relative to peak hours average. Similarly, Gu *et al.* (2020) use the DID approach to estimate the effect of urban rapid transit rail systems (henceforth subways) on road congestion, using the opening of a subway line as an exogeneous shock.

Along the same lines, we use the opening of new subway stations located near the registered office address of P2P lending platforms as an exogenous shock.[16] After the opening of a new subway station, the cost of transportation is reduced, so information exchange and communication between a P2P lending platform and local regulators is expected to improve. Levine *et al.* (2020) use travel time between a bank's headquarters and its branches to proxy for the cost of communicating soft information; they exploit shocks to these travel times – the introduction of new airline routes – to evaluate the effect of within-bank communication costs on small-business loans.

In addition, because traffic conditions in the area improve after a new subway station opens, the difficulty and cost of travel for onsite supervision by local regulators is substantially reduced, facilitating supervision and improving the monitoring of P2P lending platforms. Therefore, we expect the openings of new subway stations near P2P lending platforms to reduce the collapse rate of those platforms.

The cities where most platforms in our sample are located have experienced new subway station openings. Additionally, thanks to the rapid development of subway systems in major Chinese cities, there are sufficient new subway stations openings throughout our sample period, enabling us to use subway openings in our research design.

We use the events in which a new subway station opened within 1 kilometre of a P2P lending platform's office because people rarely walk farther than that to take the subway. However, as a subway station mainly affects nearby traffic conditions, it is reasonable to assume that ground traffic conditions within 1 kilometre greatly improve after the opening of a new subway station. Given that the subway stations near the various P2P lending platforms opened at different times, we follow Beck *et al.* (2010) and Jiang *et al.* (2016) in adopting a time-varying DID method. If a platform was operating before the nearest subway station within 1 kilometre opened, the platform is in the treatment group. This setting ensures that the P2P lending platforms in our treatment group experienced the effect of the subway opening.

We examine the effect of new subway stations near the P2P lending platforms by performing a time-varying DID analysis using the following regression:

$$Collapse_{i,t} = \beta_0 + \beta_1 Subway1km_i \times AfterOpen_i + \beta_2 Subway1km_i + \beta_3 Control_{i,t} + Prov_i + Year_i + \varepsilon_{i,t}, \tag{4}$$

where i indexes the P2P lending platform, and t indexes the year. $Collapse_{i,t}$ denotes whether

[16] In mainland China, total subway length increased from less than 200 km in 2000 to over 6,700 km in 2019. At the end of 2019, there were 211 urban rail transit lines in 40 cities in mainland China, according to https://en.wikipedia.org/wiki/Urban_rail_transit_in_China, which provides suitable data for the empirical analysis in this section.

P2P lending platform *i* collapsed in year *t*. $Subway1km_i$ is a dummy variable that equals one if the nearest subway station is within a straight-line distance of 1 kilometre of the P2P lending platform *i* and that the platform *i* was operating before the opening of subway station, and zero otherwise.[17] The control group includes P2P lending platforms not having a nearby subway opening within 1 kilometer. $AfterOpen_i$ is a dummy variable that indicates when the subway station nearest P2P lending platform *i* opened. It equals one for observations after the station opened and zero otherwise. We control for other variables that might affect P2P lending platforms' collapse, including platform- and city-level control variables and provincial ($Prov_i$) and year ($Year_i$) fixed effects. $\varepsilon_{i,t}$ is the random disturbance term.

[------ Insert Table 5 Panel A here -----]

Panel A in Table 5 reports the results of the time-varying DID analysis. In Column (1), the full sample is used for the regression analysis. To eliminate the influence of these potential biases, we set the time window to be [-3, 3] years around the subway opening events in Column (2). We find that the coefficients on the interaction term (*Subway1km*×*AfterOpen*) are negative and statistically significant at the 1% level.

To further control for any omitted unobservable variables, we adopt the PSM-DID method using the nearest neighbour matching method with a 1:4 treatment to control ratio. Column (3) shows the regression results using the matching sample, using a sample window of [-3, 3] years around the subway opening events. The empirical results show that the coefficient on *Subway1km*×*AfterOpen* is still negative and statistically significant at the 1% level. Overall, our empirical results confirm that the openings of new subway stations significantly reduce the collapse rate of P2P lending platforms.

To ensure the validity of these results, we analyse the dynamic trend of the effect of new subway stations near the P2P lending platforms. Specifically, we estimate the following equation:

$$Collapse_{i,t} = \beta_0 + \beta_1 Subway1km_i \times Before2yr_{i,t}^{-2} + \beta_2 Subway1km_i \times Before1yr_{i,t}^{-1} + +\beta_3 Subway1km_i \times After1yr_{i,t}^{1} + \beta_4 Subway1km_i \times After2yr_{i,t}^{2} + +\beta_5 Control_{i,t} + Prov_i + Year_i + \varepsilon_{i,t}, \quad (5)$$

where $Before1yr_{i,t}^{-1}$ ($Before2yr_{i,t}^{-2}$) is a dummy variable that equals one if the platform-year observation is at least one year (or two years) before the subway station nearest the P2P lending platform opened and zero otherwise. $After1yr_{i,t}^{1}$ ($After2yr_{i,t}^{2}$) is a dummy

[17] Figure IA 11 in the Internet Appendix provides an example of a P2P platform in our treatment group.

variable that equals one if the observation occurs at least one year (or two years) after the nearest new subway station around the P2P lending platform was opened, and zero otherwise. All of the other variables are the same as those described in the baseline time-varying DID regression. The coefficients of interest are β_1 and β_2.

[------ Insert Table 5 Panel B here -----]

We report the dynamic DID results in Panel B of Table 5. Our focal variable is the interaction term of $Subway1km_i$ with $After1yr_{i,t}^1$. We find that in the first year after a new subway station opens, the coefficient on the interaction term β_3 is significantly negative, implying that the new subway station reduced the likelihood of the P2P lending platform collapsing. The coefficients β_1 and β_2 are statistically insignificant in all of the regressions, indicating that the parallel trend assumption of the time-varying DID design is satisfied.

Figure IA 12 illustrates the time trends of the collapse rates of the treatment and control groups before and after new subway station openings, which shows that the collapse rates of the platforms in the treatment and control groups before new subway station openings are comparable.

Similar to the previous section, we conduct a balance test on platform characteristics between the treatment and control groups in the DID analysis. We find no significant difference in these characteristic variables between the P2P lending platforms in the treatment and matched control groups, indicating that the two groups are similar in platform characteristics and only differ in whether a new subway station opened nearby. We report these test results in Table IA 4.

For robustness, we conduct two placebo tests by changing the key parameters in the DID analysis. In the first placebo test, we set P2P lending platforms that are 1-2 km (*Subway1_2km*), 2-3 km (*Subway2_3km*), and 3-4 km (*Subway3_4km*) away from the nearest subway station and have been established before the opening of the subway as pseudo-treatment groups. If the new subway station is more than 1 kilometre from the P2P lending platform's office, we expect its opening not to have a significant effect on the traveling to the platform's office. The DID test result using these placebo groups are reported in Internet Appendix Table IA5, which shows statistically insignificant effects of subway opening in over 1 kilometre away, implying that more distant subway openings do not affect platform collapses.

Second, we conduct a simulation that randomly selects the year when a new subway station opened near the platforms in the treatment group. Specifically, in each simulation, we randomly assign a year within the sample period to each P2P lending platform in the treatment group and use it as the year a subway station opened nearby. Then, we conduct our baseline DID test using this pseudo-event year, and we repeat this process 5,000 times.

In Table IA 6 in the Internet Appendix, we summarise the distribution of the coefficients and *p*-values of *Subway1km×AfterOpen* from the time-varying DID regressions by reporting the mean, 5th percentile, 25th percentile, median, 75th percentile, and 95th percentile. We find that the mean coefficient on the interaction term is negative but insignificant, with a *p*-value much higher than 10%. The mean value is -0.011 for the placebo tests, statistically insignificant, which is quite different from the actual estimated coefficient of -0.152. The placebo test results provide evidence that the openings of new subway stations have a causal effect on P2P lending platform collapse.

4.4 Instrumental variable analysis

Our results may suffer from potential endogeneity concern due to omitted variables related to platform quality. For instance, some P2P lending platforms are established with the intention of scamming investors, so they naturally have a higher collapse rate. To address this endogeneity concern, we take the instrumental variable approach, using the number of streets (*Street*) passed when driving from the local regulatory office to the P2P lending platform's office as an instrument variable.

This instrument meets the two validity requirements. First, the number of streets (*Street*) that one needs to pass when driving from the local regulatory office to the P2P lending platform's office affects the driving distance (*DriveDistance*) and the driving time (*DriveTime*) between the two locations. Theoretically, the number of streets to pass is positively correlated with travel time and travel distance. Second, the number of streets passed does not have a direct effect on the collapse rate of P2P lending platforms.

[------ Insert Table 6 here -----]

We present the first-stage regression with *DriveDistance* and *DriveTime* as the dependent variables and the instrument as the main explanatory variable in Columns (1) and (3) of Table 6. The same set of independent variables used in Table 3 is included in both the first- and second-stage IV tests. In addition, considering that the straight-line distance between the two places also affects the driving distance and time, we further control the straight-line distance between the local regulatory office and a P2P lending platform (*StraightDistance*). We find that the coefficient estimates on *Street* are positive and significant at the 1% level, suggesting that *Street* is positively associated with *DriveDistance* and *DriveTime*. Moreover, the *F*-statistics are 2,964 and 1,730, rejecting the null hypothesis that the coefficient on the instrument is insignificantly different from zero at the 1% level, mitigating the weak instrument concern.

The second-stage regression results are reported in Columns (2) and (4) of Table 6 and are consistent with the baseline estimation results. The coefficients on *DriveDistance* and *DriveTime* are positive and significant at the 5% level. The results for the Wald test of the exogenous null hypothesis are provided at the bottom of the table, with *p*-values of 0.01 and 0.017, respectively, indicating that the null hypothesis is rejected and that *DriveDistance* and *DriveTime* can be considered endogenous variables at the 5% level. Overall, our IV probit estimation results confirm the robustness of our main results.

5. Additional tests

5.1 Economic mechanisms

In this section, we explore two plausible economic channels through which regulatory distance affects the collapse of P2P lending platforms: the information exchange and resource constraint channels. The detailed channel mechanisms are elaborated below.

5.1.1 Information exchange channel

Geographic proximity enables regulators to monitor firms more effectively because they can obtain soft information through informal channels at a low cost, and it reduces information asymmetry among market participants (Agarwal & Hauswald 2010). As China's fintech industry only emerged in early 2010, most P2P lending platforms are young start-ups. Consequently, the information environment of P2P lending platforms is less transparent and accessible to market participants and regulators, compared with listed firms. Listed firms issue more hard information to the public. For example, their financial statements are audited by third-party institutions and filed with government regulatory commissions.

For start-up fintech firms such as P2P lending platforms, their operations and performance are highly opaque to market participants. Information on their corporate governance, risk controls, business compliance, and actual operating conditions are not easily accessible to external parties. Soft information is especially important when hard information is less available to market participants or supervisory authorities. As documented in Bertomeu and Marinovic (2016) and Liberti and Petersen (2019), the collection of soft information is difficult and involves higher costs than the collection of hard information.

We hypothesize that regulatory distance affects the collection of soft information about

P2P lending platforms. A shorter regulatory distance reduces the degree of information asymmetry between a P2P lending platform and its local regulatory office. For the local regulatory office, the closer the platform, the more convenient it is to obtain soft information. Similarly, the management of the platform can better understand the regulatory environment and the policies of the local regulatory office, so they can adjust to meet its requirements. Geographic proximity also helps build trust between the regulatory authority and its surrounding P2P lending platforms.

In this section, we examine the onsite inspections of P2P lending platforms by local government leaders as an information exchange channel through which regulatory distance affects platforms' collapse. Onsite supervision of P2P lending platforms by local regulators is irregular, and detailed reports about such onsite supervision are not disclosed. Therefore, we cannot obtain detailed official schedules or information about the onsite visit activities of local regulators. However, visits and onsite inspections of P2P lending platforms by local government leaders are usually publicly announced. Hence, we can obtain this information through official announcements and reports.[18] To collect this information, we use the Baidu search engine (Baidu.com) and the following search terms: 'government leaders' + 'platform name' + 'site inspection.'[19]

We construct a variable *Onsite* to test the information exchange channel based on the local government onsite inspection data. $Onsite_{i,t}$ is a dummy variable that equals one if there is any onsite inspection by any local government leader of P2P lending platform *i* in year *t* and zero otherwise. To test the influence of regulatory distance on the intensity of government officials' onsite inspections, we follow the mediation procedures outlined in Baron and Kenny (1986), which involve estimating the following three regressions:

$$Onsite_{i,t} = \alpha_0 + \alpha_1 Distance_i + \alpha_2 Control_{i,t} + Prov_i + Year_i + \varepsilon_{i,t}, \quad (6)$$

$$Collapse_{i,t} = \gamma_0 + \gamma_1 Onsite_{i,t} + \gamma_2 Distance_i + \gamma_3 Control_{i,t} + Prov_i + Year_i + \varepsilon_{i,t}, \quad (7)$$

where *i* indexes the P2P lending platform, and *t* indexes the year. $Collapse_{i,t}$ denotes whether P2P lending platform *i* collapsed in year *t*. It is a dummy variable that equals one if P2P lending platform *i* collapsed in year *t* and zero otherwise. Information exchange activities are proxied using $Onsite_{i,t}$. $Distance_i$ denotes regulatory distance, including the driving distance (*DriveDistance*) and the driving time (*DriveTime*) between the local regulatory office and P2P

[18] China's P2P lending platforms are not considered financial institutions, in addition to onsite inspections from local regulatory offices, they must also comply with the supervision of other local government departments, such as the Market Supervision Administration and the Bureau of Industry and Information Technology.

[19] Figure IA 13 in the Internet Appendix presents two inspections by local government leaders.

lending platform *i*. We control for other variables that might affect the collapse of P2P lending platforms, including platform- and city-level characteristics and provincial (*Prov$_i$*) and year (*Year$_i$*) fixed effects. $\varepsilon_{i,t}$ is the random disturbance term.

Our approach is conceptually similar to a path analysis (Pevzner *et al.* 2015; Hilary *et al.* 2016; Jiang *et al.* 2018; Chen *et al.* 2019), commonly used in testing how a variable (*Distance* in our case) affects another variable (*Collapse* in our case). The effect works through a mediating variable (*Onsite* in our case). The coefficient α_1 in Equation (6) is the effect of *Distance* on the mediating variable (*Onsite*), and γ_1 is the effect of the mediating variable (*Onsite*) on the dependent variable (*Collapse*), after controlling for the influence of the independent variable (*Distance*). A significant α_1 or γ_1 would imply that the mediating effect is significant (James & Brett 1984; MacKinnon *et al.* 2007; Zhao *et al.* 2010).

We expect regulatory distance to affect the collapse of P2P lending platforms by affecting information exchange. The greater regulatory distance, the higher the cost of information exchange between regulatory authorities and P2P lending platforms is, which creates hurdles for information transmission. Hence, we expect α_1 to be positive. Then, the likelihood of information exchange affects the operation of P2P lending platforms. P2P lending platforms with information advantages understand the local regulatory environment and policies in a timely manner and adjust to meet the requirements of local regulators, reducing the likelihood of collapse. Accordingly, γ_1 is expected to be negative.

Table 7 reports the logit regression results on the effect of *DriveDistance* and *DriveTime* on the likelihood of *Onsite* supervisory visits. Consistent with our expectation, the coefficients on *DriveDistance* and *DriveTime* are significantly negative at the 10% confidence level, implying that a greater regulatory distance significantly reduces the likelihood of onsite inspection by local government leaders. Greater regulatory distance reduces the likelihood of information exchange between P2P lending platforms and regulatory authorities.

[------ Insert Table 7 here -----]

In Columns (3) and (4), the coefficients on *Onsite* are significantly negative at the 5% confidence level. These results show that the likelihood of onsite inspections by local government leaders can significantly reduce the possibility that a P2P lending platform collapses. This finding confirms that the likelihood of information exchange between local regulators and P2P lending platforms play an important role in the collapse rate of P2P lending platforms.

Overall, we find that greater regulatory distance significantly reduces the likelihood of local government leaders' onsite inspections of P2P lending platforms. Greater regulatory distance makes it harder for regulators to collect relevant soft information about P2P lending platforms, aggravating the information asymmetry between the regulator and P2P lending platforms. This suggests that information exchange between government officials and P2P lending platforms via onsite inspections is a plausible channel for regulatory distance to affect the collapse of P2P lending platforms.

5.1.2 Resource constraint channel

Kedia and Rajgopal (2011) study the effect of SEC enforcement preferences on corporate misconduct. They find that firms located closer to SEC officials are more likely to be investigated when SEC regulators face resource constraints. Regulatory distance increases supervision costs in that greater regulatory distance requires more resources in terms of transportation time and cost, personnel, etc. Given the limited budgets of local regulatory agencies, their supervision activities are restricted and only limited resources can be allocated to regulating the P2P industry.

In this section, we use the financial supervision expenditures of the local government in the province where the P2P lending platform is located to examine the effect of budget constraints on regulatory distance. Local financial supervision expenditures are expenses incurred by local governments in financial supervision activities. We divided the financial supervision expenditure in China's provincial statistical yearbook by the number of P2P lending platforms in each province in that year (*RegExp*) to measure the average expense incurred by local governments in financial supervision activities for each P2P lending platform in that year.

We expect a greater regulatory distance to be associated with higher regulatory monitoring expenses. Given limited budgets, local offices with greater budgets can more easily conduct supervision activities, all else being equal. Hence, resource constraints are one of the channels through which regulatory distance may affect platform collapse. We expect greater financial regulatory related spending to weaken the impact of regulatory distance on the collapse of P2P lending platforms.

To test the effect of the resource-constraint channel on regulatory distance, we estimate the following regression models:

$$Collapse_{i,t} = \gamma_0 + \gamma_1 RegExp_{p,t} \times Distance_i + \gamma_2 Distance_i + \gamma_3 RegExp_{p,t} + \gamma_4 Control_{i,t} + Prov_i + Year_i + \varepsilon_{i,t}, \quad (8)$$

where p indexes the province where the P2P lending office is located, i indexes the P2P lending platform, and t indexes the year. $Collapse_{i,t}$ is a dummy variable that equals one if P2P lending platform i *has* collapsed in year t and zero otherwise. $RegExp_{p,t}$ is defined as the financial regulatory expenditure of each province divided by the number of P2P lending platforms in each province that year. $Distance_i$ denotes regulatory distance, including driving distance (*DriveDistance*) and driving time (*DriveTime*) between the local regulatory office and P2P lending platform i. We control for other variables that could affect the collapse rate of P2P lending platforms, including platform- and city-level characteristics and provincial ($Prov_i$) and year ($Year_i$) fixed effects. $\varepsilon_{i,t}$ is the random disturbance term.

We then test the resource constraint channel based on equation (8). Resource constrained regulators will not be able to adequately supervise the platforms, which may lead to more platform collapses. Conversely, regulators with more resources could deploy more resources for monitoring and supervision, reducing the likelihood of platform collapse. Hence, we expect γ_1 to be negative.

[------ Insert Table 8 here -----]

Table 8 reports the estimation results. Our key explanatory variables in Columns (1) and (2) are *DriveDistance×RegExp* and *DriveTime×RegExp*, respectively. The results show that the coefficients on these two interaction terms are significantly negative, implying that greater regulatory resources invested by financial regulatory authorities on supervision could effectively attenuate the positive impact of *DriveDistance* on the likelihood of collapse. Overall, this result supports our conjecture that resource constraints are a potential channel through which regulatory distance affects the collapse rate of P2P lending platforms.

5.2 The influence of regulatory discretion: 2016 policy shock

On August 24, 2016, the China Banking Regulatory Commission issued "Interim Measures for the Administration of the Business Activities of Online Lending Information Intermediary Institutions", establishing the position of P2P lending platforms in the financial market and clarifying the related roles and responsibilities of supervisory bodies and rules for borrower and investor protection and information disclosure. In particular, Clause 33 clearly stipulates that each local financial supervision department is responsible for the institutional supervision of the online lending platforms in their jurisdictions, such as normal guidance, filing management, risk prevention, and disposal work. This publication strengthened the regulation of the P2P lending industry, leading to a reshuffling of the industry.

Before this clarification, all levels of local governments had financial regulatory agencies, but the rules for regulating emerging fintech companies such as P2P lending platforms were undefined. Therefore, local regulatory offices could exercise discretion in their supervision of such platforms (Duflo *et al.* 2018).[20] For example, they could choose to conduct few (or no) supervisory activities for more distant P2P lending platforms because of the costs involved.

After August 2016, responsibility for the supervision of P2P lending platforms clearly belonged to local financial authorities, regardless of *the distance* between a P2P lending platform and the local regulatory office. Therefore, after the policy clarification, we expect the effect of regulatory distance on the collapse of P2P lending platforms to be weakened (Gennaioli & Rossi 2010; Bowen *et al.* 2013).

To test the above conjecture, we estimate the following logit regression model:

$$Collapse_{i,t} = \beta_0 + \beta_1 Distance_i \times Policy_t + \beta_2 Distance_i + \beta_3 Control_{i,t} + Prov_i + Year_i + \varepsilon_{i,t}, \quad (10)$$

where i indexes the P2P lending platform, and t indexes the year. $Collapse_{i,t}$ denotes whether platform i collapsed in year t. $Distance_i$ is the regulatory distance variable, which includes driving distance (*DriveDistance*) and driving time (*DriveTime*) between the local regulatory office and P2P lending platform i. $Policy_t$ is a dummy variable that equals one for observations in the 2017-2019 post-policy period and zero otherwise. We control for other variables that might affect P2P lending platform collapse, such as platform- and city-level control variables. We also include provincial ($Prov_i$) and year ($Year_i$) fixed effects in the regression. $\varepsilon_{i,t}$ is the random disturbance term.

[------ Insert Table 9 here -----]

Table 9 reports the estimation results, and the regression results for the interaction of *Collapse* with *DriveDistance×Policy* and *DriveTime×Policy* are presented in Columns (1) and (2), respectively. We find that the coefficients on *Policy* are positive and statistically significant at the 1% level, indicating that the overall collapse rate of P2P lending platforms significantly increased after the policy. This is consistent with the rationale that stringent supervision causes platforms without prudent risk management and those involved in fraud to exit the industry.

Importantly, the coefficients on the interaction terms (*DriveDistance×Policy* and *DriveTime×Policy*) are negative and statistically significant. This is consistent with our expectation that after the implementation of the regulatory policy, local regulators better

[20] Note that local financial supervision departments belong to the civil service system, not the professional financial supervisory agency. The civil service system generally discourages risky adventures such as P2P lending, an industry that has experienced waves of collapse since 2016. Therefore, regulatory responsibility for P2P lending platforms is entrusted to local financial regulatory authorities and are enforced by local governments.

monitored P2P lending platforms, weakening the effect of regulatory distance on the collapse of P2P lending platforms.

5.3 Types and operation time of P2P lending platform collapse

There are two main types of collapse for Chinese P2P lending platforms: fraud-related collapse and benign exits. As its name implies, the first type involves fraud and malicious scams where a P2P lending platform is usually suspected of illegal activities. Typically, the platform just terminates its operation without proper advanced notice or follow-up compensation procedures for its investors. This type of collapse usually results in substantial losses for the investors and negative impact for the industry, which regulators try to avoid. The second type is a benign exit, which involves a P2P lending platform liquidating its assets and closing down its operations in an orderly manner. During a benign close-down, the assets of a P2P lending company are liquidated to repay investors and any outstanding liabilities, which very much resembles a bankruptcy.

In this section, we further distinguish the types of platform collapse and examine the effects of regulatory distance on the collapse rate of each type. We expect greater regulatory distance to be associated with a lower likelihood of benign exit and a higher likelihood of fraud-related exit.

Table 10 reports the regression estimation results by collapse type. We control for city-level characteristics in the year of the collapse and year fixed effects. Columns (1) and (2) show the estimated effect of *DriveDistance* and *DriveTime* on the likelihood of benign exit. *Benign* is defined as whether the collapsed P2P lending platform *i* had a benign exit. The coefficients on *DriveDistance* and *DriveTime* are both significantly negative at the 1% confidence level, indicating regulatory distance significantly reduces the likelihood of a benign exit for P2P lending platforms.

This result supports our main hypothesis that regulatory proximity, as proxied by a closer physical distance, facilitates information acquisition and promotes a more transparent information environment. When platforms are about to collapse, a better information environment promotes information sharing between the platform and the local regulators, enabling the formulation of an exit plan and increasing the likelihood of a benign exit.

[------ Insert Table 10 here -----]

Next, we look at how regulatory distance affects fraud-related collapse. *Fraud* is defined as whether the collapsed platform *i* was involved in fraud. The results for the regression of

DriveDistance and *DriveTime* on *Fraud* are presented in Columns (3) and (4). The coefficient on *DriveDistance* is positive (0.085) and significant (z = 2.17) at the 5% level. Similarly, the coefficient on *DriveTime* is positive (0.079) but weakly significant (z = 1.54) at almost the 10% significance level. Overall, our results indicate that regulatory distance significantly increases the likelihood of fraud related collapse, consistent with the rationale that greater regulatory distance is associated with less supervisory guidance, resulting in a greater likelihood of fraud-related collapse.

Besides looking at the collapse likelihood, we also examine the survival time of P2P lending platforms. The survival time *SurvivalTime* is defined as the log of the number of days between the P2P lending platform going online and collapse, which is a continuous variable potentially convey more information than the dichotomous collapse indicator.

Columns (5) and (6) reports the estimation results for the effect of regulatory distance on survival time, controlling for city-level characteristics in the year of the collapse and year fixed effects. We find that the coefficients on *DriveDistance* and *DriveTime* are both significantly negative at the 1% confidence level, indicating regulatory distance significantly reduces the survival time of the collapsed P2P lending platform. This result implies that lower regulatory intensity reduces the survival time, consistent with earlier result that greater distance leads to higher collapse rate.

5.4 Additional robustness tests

5.4.1 Alternative regulatory distance variables

First, we use straight-line distance instead of travel distance as an alternative proxy for regulatory distance. We use latitude and longitude to calculate straight-line distance (*StraightDistance*) and the altitude of the city (*Altitude*) to capture terrain differences between cities. *StraightDistance* is significantly positive at the 1% level, confirming the robustness of our baseline result. We report these results in Column (1) of Table IA 7 in the Internet Appendix.

Second, we use the average driving distance and driving time as alternative measures of regulatory distance and cost. As some roads are one-way only, the driving distance and time from locations A to B could differ from those from B to A. Therefore, the driving distance and time between the local regulatory office and a P2P lending platform's office may vary depend on the traveling direction.

To address this concern, we use the average value of the driving distance (*Ave_DriveDistance*) and driving time (*Ave_DriveTime*) from the local financial regulatory office to the P2P lending platform and from the P2P lending platform to the local financial regulatory office as our independent variables. As shown in Columns (2) and (3) of Table IA 7 in the Internet Appendix, *Ave_DriveDistance* and *Ave_DriveTime* are significantly positive at the 1% level.

The third set of alternative measures comprises relative driving distance and time and . Among Chinese cities, there are large variations in terms of area size. For a larger city (Beijing covers 16,410.54 square kilometres), 17 kilometres (the average value of *DriveDistance* in the sample) is not a particularly long driving distance. For a relatively small city (Shenzhen is 1,997.47 square kilometres), 17 kilometres may be a relatively long driving distance. Therefore, we divide *DriveDistance* and *DriveTime* by the logarithm (*lnArea*) of the area of the city where in 2015 the P2P lending platform was located to get relative driving time (*Relative_DriveDistance*) and relative driving distance (*Relative_DriveTime*), which are our independent variables. The empirical results show that *Relative_DriveDistance* and *Relative_DriveTime* are positively significant at the 1% level, which is significantly positive. We report these results in Columns (4) and (5) of Table IA 7 in the Internet Appendix.

5.4.2 Using Cox Proportional Hazard and OLS as alternative estimation methods

Note that the platform collapse variable is right censored because once a P2P lending platform collapses in any year, it is no longer included in our sample. Although we have used the logit model in our main analysis, we also use the Cox proportional hazard model as a robustness test to deal with the right censoring issue commonly encountered in survival analysis (Cox 1972; Hyde 1977; Lagakos 1979; Frangakis & Rubin 1999). The hazard model estimation results in Internet Appendix Table IA 6 show that *DriveDistance* and *DriveTime* still have a positive and significant effect on collapse rate.

One potential issue with the Logit model is that the bias of the FE estimator in nonlinear models. The previous research points out that in the estimation of nonlinear models such as logit model, the direct control of fixed effects will result in a statistically so-called “incidental parameter problem” (Neyman & Scott 1948; Greene 2004). To address this potential estimation bias, we repeat our main analysis using the OLS regression model as a robustness test, which is reported in Internet Appendix Table IA 8. We obtain consistent results that *DriveDistance* and *DriveTime* still have a positive and significant effect on platform collapse rate.

5.4.3 Subsample analyses

The spatial distributions of the platforms, as shown in Figures 2 and 3, reveal that majority of P2P lending platforms in our sample are from developed regions in eastern China. Specifically, 3,359 (1,032 unique platforms) of the 18,044 platform-year observations in our sample are from the Guangdong province. Beijing and Shanghai have 2,699 (753 unique platforms) and 2,375 (765 unique platforms) platform-year observations, respectively. One may be concerned that our results could be affected by such concentration in the sample composition.

To address this issue, we conduct a subsample analysis by excluding observations from Guangdong province, Beijing, and Shanghai as a robustness check. We re-estimate the baseline regression result using the subsample and report these results in Internet Appendix Table IA 9-1. We find that the coefficients on *DriveDistance* and *DriveTime* remain positive and significant at the 1% level. Similarly, *DriveDistance* and *DriveTime* remain significantly positive at the 10% level using the reduced sample, which alleviates the sample concentration concern.

Another subsample analysis we conduct is based on sample periods. There is an overall increased rate of collapse after 2016, as shown in Table 2. This higher collapse rate could be due to the tightened regulatory scrutiny after 2016, when China's financial regulatory authorities had clarified on the regulatory body for P2P lending platforms. To address this potential concern that our results may be confounded by tighter regulation after 2016, we split the sample into two subperiods: 2007-2015 and 2016-2019, and re-estimated our baseline regression for each subsample. The regression results are presented in Internet Appendix Table IA 9-2, which show consistent result that *DriveDistance* and *DriveTime* still have a positive and significant effect on collapse rate.

5.4.4 Including controls on distance to other regulatory bodies

Thus far, we have examined the role of local regulators. A natural question arises about the role of other regulatory bodies such as the National People's Congress and the Chinese People's Political Consultative Conference. In nominal terms, municipal people's congresses have the power to appoint and remove municipal government leaders and to supervise the municipal government, procuratorates, and courts. Similarly, the Chinese People's Political Consultative Conference at the municipal level is a way to include other party groups (non-communist parties) and people from all walks of life in the supervision and advising of municipal government agencies and staff.

To examine potential monitoring by other central authorities, we further control for the following variables: *CongressDriveDistance* and *CongressDriveTime,* defined as the driving distance and time between the National People's Congress where a P2P lending platform is located and the platform; and *CppccDriveDistance* and *CppccDriveTime*, defined as the driving distance and time between the Chinese People's Political Consultative Conference where a P2P lending platform is located and the platform.

After adding these indicators to the benchmark regression, we find that *DriveDistance* and *DriveTime* remain significantly positive at the 1% level, whereas *CongressDriveDistance, CppccDriveDistance, CongressDriveTime* and *CppccDriveTime* are not significant. This shows that our baseline results are robust to considering the supervisory role of other regulatory bodies. These results are reported in Table IA 10 in the Internet Appendix.

5.4.5 Additional control variables for location factors

In this section, we further control for locational amenities such as adjacency to commercial districts or shopping centres to alleviate potential endogeneity concern due to omitted variables. We use three variables to capture the locational effects of P2P lending platforms. The first variable is the straight-line distance between the P2P lending platform and the nearest coffee shop (*NearestCoffeeShop*), and the second variable is the straight-line distance between the P2P lending platform and the nearest bar (*NearestBar*). We also control for a third variable, the straight-line distance between the P2P lending platform and the nearest commercial pedestrianised street (*NearestPedestrianmall*). Generally, the pedestrianised street in a Chinese city marks the city's central commercial district, and it is usually also a relatively prosperous area, such as Nanjing Road in Shanghai and the Ginza district in Tokyo. The farther a P2P lending platform is from these amenities, the more suburban it is.

After controlling for these three variables in the baseline regression, we find that *DriveDistance* and *DriveTime* remain significantly positive at the 1% level. This further shows that the baseline results are robust and not affected by other locational factors of P2P lending platforms' offices. We report these results in Table IA 11 in the Internet Appendix.

6. Conclusion

The large-scale collapse of P2P lending platforms in China prompts us to investigate the role of government regulation in the fintech industry. In this paper, we examine the role of regulatory monitoring on the collapse rate of P2P lending platforms. We focus on regulatory distance, defined as the geographic distance between a P2P lending platform and the local regulatory office, as a key measure of the monitoring intensity by regulators. Our analysis shows that less regulatory monitoring, proxied by both the geographic distance and the driving time between the local regulatory authority and the P2P lending platform, significantly increases the probability of the P2P lending platform's collapse.

In addition to the baseline analysis, we devise two main identification strategies to establish causality: the DID analysis and the instrumental variable approach. First, we use the DID test approach with two policy shocks: the relocation of Hangzhou government office and the opening of new subway stations. Second, we use the number of streets that are passed when driving from the local regulatory office to the P2P lending platform as an instrument variable. After a battery of robustness tests, the main conclusions remain valid.

We then explore the channels through which regulatory distance affects the collapse likelihood of P2P lending platforms, namely information exchange and resource constraints. Furthermore, we find that the increased regulatory distance reduces the probability of a benign exit and increases the probability of a fraud collapse. Overall, our findings support our hypothesis that geographic distance plays an important role in regulating new types of fintech firms.

This study has important policy implications for financial regulators responsible for supervising digital financial services. Financial regulatory authorities should maintain timely communication and exchange with companies in financial innovations, fully understand the development trends of new types of financial innovations and collect comprehensive industry-level information in formulating industry regulatory policies. This study also implies that supervision and monitoring in the form of *onsite* visits is particularly valuable in the regulation of *online* platforms. Local financial regulators should combine online and offline supervision modes in the regulation of fintech firms.

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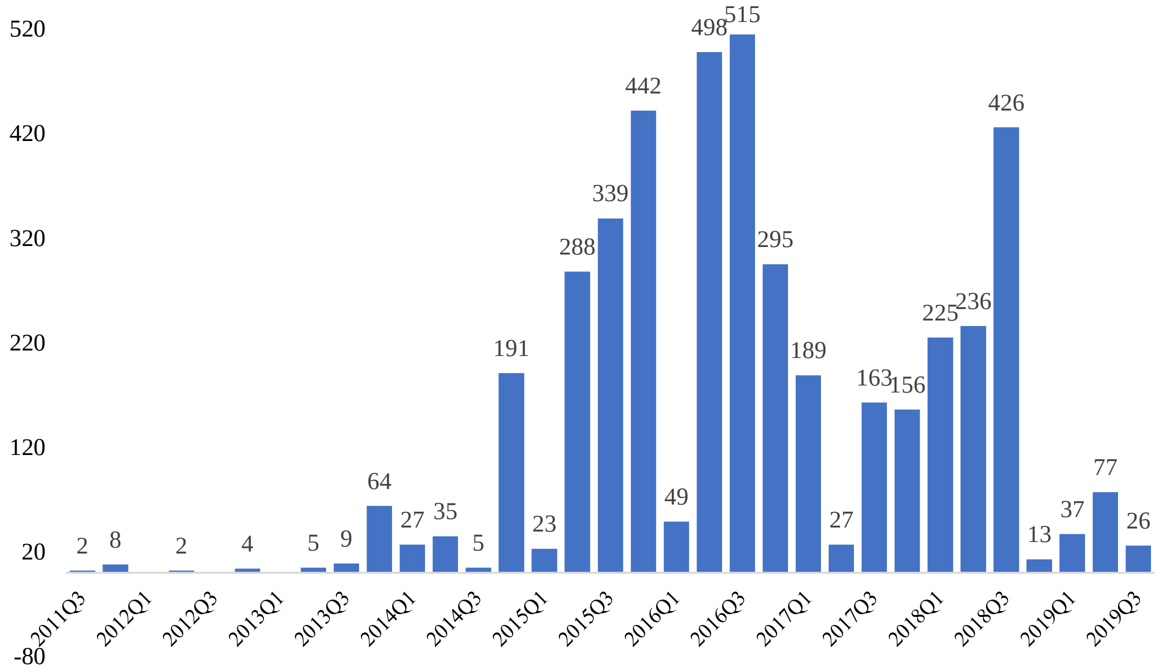
Figure 1: Number of P2P platforms over time

This figure plots the number of collapsed P2P lending platforms every quarter from 2011 to 2019. The data is from "www.wdzj.com" and CSMAR.

Panel A: Number of P2P platform collapse



Panel B: Number of P2P platforms in operation

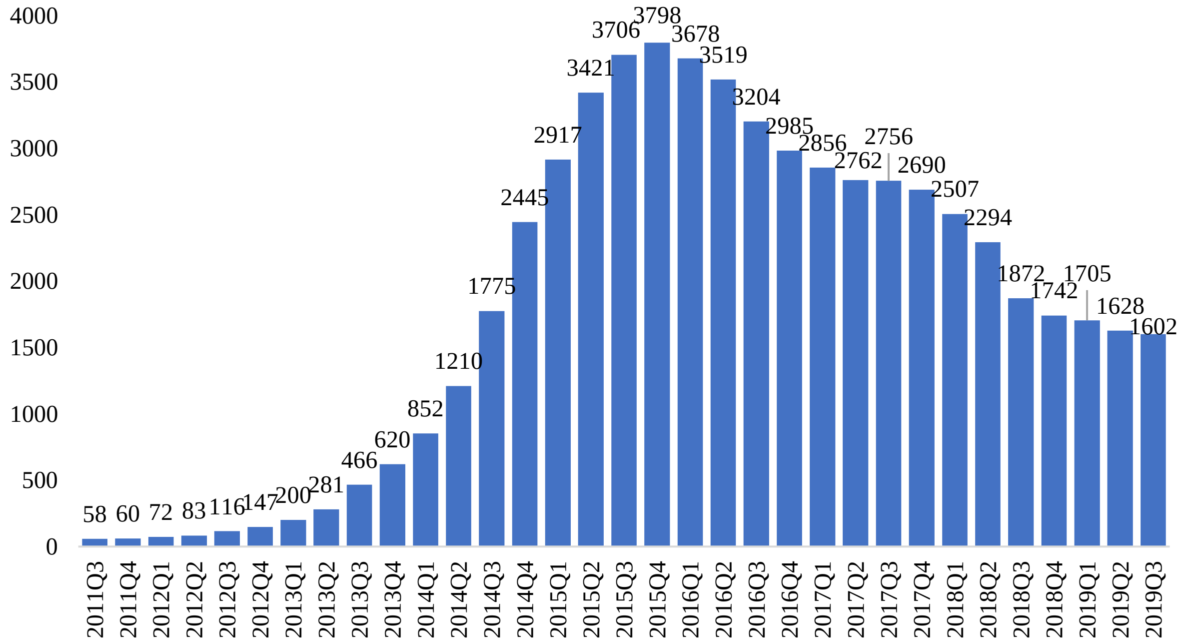


Figure 2: Geographical distribution of P2P platform collapses

This heatmap presents the average collapse rate at the province level during the sample period from 2007 to 2019. We use darker blue color to indicate higher collapse rate at the province level, and lighter blue to indicate lower collapse rate.

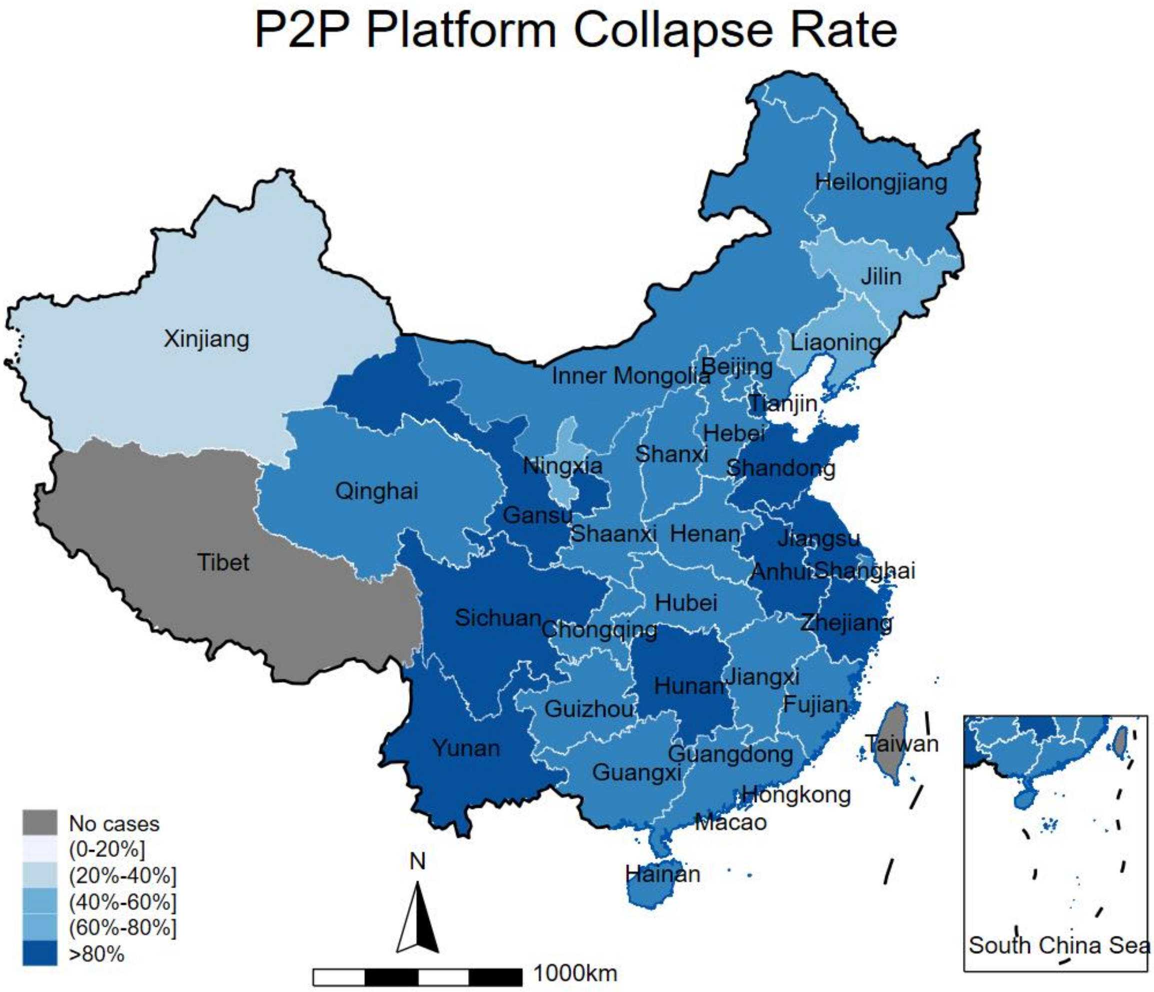
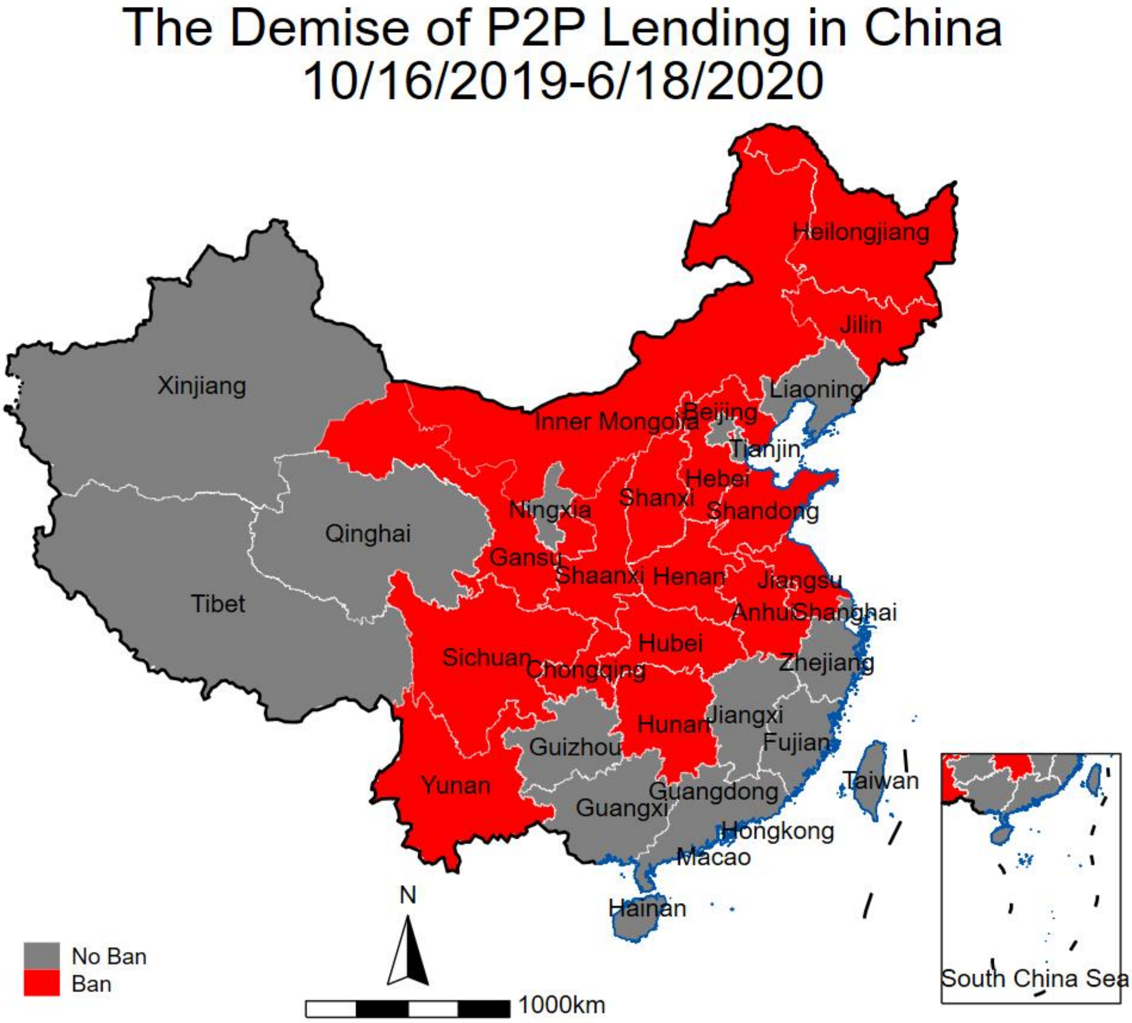


Figure 3: Distribution of provinces that banned P2P lending

The figure shows the distribution of provinces that banned all P2P lending platforms from their jurisdictions between Oct 16, 2019 and Jun 18, 2020 under the strong supervision. Regions in red are those provinces with bans on P2P platforms, whereas regions in gray are provinces without such bans.



Appendix 1: Variables Definitions

Variable	Definition
Collapse	Dummy variable, which takes the value of one if the P2P platform fails, and zero otherwise
DriveDistance	The natural logarithm of the driving distance between P2P platform and local financial office (City level), in kilometers
DriveTime	The natural logarithm of the driving time between P2P platform and local financial office (City level), in minute
DistanceBank	The natural logarithm of average straight-line distance between the platform and the city headquarters of Bank of China, Agricultural Bank of China, Industrial and Commercial Bank of China and China Construction Bank
RegCapital	The natural logarithm of the registered capital of the P2P platform, in RMB million
Collateral	A dummy variable which takes the value of one if P2P platform is engaged in mortgage business, and zero otherwise
CapitalDeposit	A dummy variable which takes the value of one if the funds of P2P platform users need to be deposited by the bank institution, and zero otherwise
RiskDeposit	A dummy variable which takes the value of one if the risk reserve fund of P2P platform is deposited by the bank institution, and zero otherwise
GDP/PC	The natural logarithm of annual per capita GDP of the city where the platform is located
Deposit/GDP	The natural logarithm of annual deposit balance divided by GDP in the city where the platform is located
Loan/GDP	The natural logarithm of annual loan balance divided by GDP in the city where the platform is located
MobilePhone/PC	The natural logarithm of the number of mobile phone users divided by the population in the city where the platform is located
Street	The number of streets that one needs to pass to drive to the P2P lending platform
Onsite	A dummy variable that takes the value of one if a local government leader inspects the P2P lending platform in a year, and zero otherwise.
RegExp	The logarithm of the annual financial regulatory expenditure for the province divided by the total number of platforms in each province
Benign	A dummy variable that takes the value of one if collapse of a platform is benign, and zero otherwise.
Fraud	A dummy variable that takes the value of one if the collapsed P2P lending platform has malicious scam or fraud, and zero otherwise.
SurvivalTime	Log value of the number of days from the platform establishment date to the collapse date.

Table 1: Summary statistics of key variables

This table presents the summary statistics of key variables used in the analysis. Refer to Appendix A for the detailed definitions of all variables in this table.

Platform-year level variables					
Variable	Mean	Sd	Min	Max	N
Collapse	0.266	0.442	0.000	1.000	18,044
DriveDistance	2.406	0.998	-3.411	5.761	18,044
Drive distance	17.883	21.396	0.033	317.800	18,044
DriveTime	2.900	0.752	0.000	5.447	18,044
Drive time	24.031	21.149	1.000	232.000	18,044
Platform level variables					
DistanceBank	2.046	1.150	-1.622	8.128	5,984
RegCapital	5.579	1.182	-1.203	11.512	5,984
Collateral	0.042	0.201	0.000	1.000	5,984
CapitalDeposit	0.180	0.384	0.000	1.000	5,984
RiskDeposit	0.022	0.149	0.000	1.000	5,984
City-year level variables					
GDP/PC	11.238	0.642	8.556	13.155	1,144
Deposit/GDP	0.628	0.422	-0.649	3.149	1,144
Loan/GDP	0.326	0.501	-1.671	2.416	1,144
MobilePhone/PC	1.293	1.189	-0.932	9.397	1,144

Table 2: Time and geographical distribution of Platforms

Panel A shows the distribution of P2P lending platforms by year and Panel B by province. The full panel sample comprises 18,044 platform-year observations from 2007 to 2019. *Newly Established* refers to the number of platforms that are newly launched for operation. *Collapse* indicates the number of failed platforms. *Benign* indicates the number of benign exit platforms. *Fraud* indicates the number of fraudulent platforms. *Other* Reason indicates the number of platforms that have closed down for other reasons.

Panel A: Distribution of established and collapsed platforms over time

			Type of Collapse					
Year	Newly Established	Collapsed	Benign Collapse	Fraud Related Collapse	Other Reasons	Cumulative New	Cumulative Collapse	Cumulative Collapse Rate
2007	1	0	0	0	0	1	0	0.00%
2008	1	0	0	0	0	2	0	0.00%
2009	10	0	0	0	0	12	0	0.00%
2010	15	0	0	0	0	27	0	0.00%
2011	43	10	0	5	5	70	10	14.29%
2012	93	6	2	4	0	163	16	9.82%
2013	551	78	4	6	68	714	94	13.17%
2014	2,128	303	7	145	151	2,842	397	13.97%
2015	2,652	1,299	52	585	662	5,494	1,696	30.87%
2016	904	1,717	118	401	1,198	6,398	3,413	53.34%
2017	420	715	111	67	537	6,818	4,128	60.55%
2018	69	1,017	146	304	567	6,887	5,145	74.71%
2019	0	140	109	12	19	6,887	5,285	76.74%

Panel B: Distribution of platform collapse by province

Province	Platform-Year Observations	Collapse	Fraud	Benign	Other
Anhui	512	341	87	31	171
Beijing	2,699	1,552	308	323	1,147
Chongqing	347	227	35	52	120
Fujian	468	275	48	40	193
Gansu	47	30	13	1	17
Guangdong	3,359	2,146	614	363	1,213
Guangxi	238	132	30	16	106
Guizhou	200	113	9	25	87
Hainan	45	27	5	3	18
Heibei	381	236	61	22	145
Henan	327	209	43	25	118
Heilongjiang	85	55	6	14	30
Hubei	540	377	67	30	163
Hunan	323	247	43	37	76
Jilin	73	27	11	3	46
Jiangsu	727	529	81	31	198
Jiangxi	264	127	18	18	137
Liaoning	190	106	16	32	84
Neimenggu	56	35	9	2	21
Ningxia	66	27	4	0	39
Qinghai	9	4	1	0	5
Shandong	1,499	1,207	336	100	292
Shanxi	123	53	28	0	70
Shanxi(northwest)	200	134	28	15	66
Shanghai	2,375	1,652	444	239	723
Sichuan	389	299	66	37	90
Tianjin	187	140	30	24	47
Xinjiang	106	27	1	4	79
Yunnan	158	131	33	34	27
Zhejiang	2,051	1,580	483	230	471
Total	**18,044**	**12,045**	**2,958**	**1,751**	**5,999**

Table 3: Regulatory distance and the collapse of P2P platforms

This table presents the Logit estimation on the effect of regulatory distance on the collapse rates of P2P platforms. Our sample consists of 18,044 platform-year observations for 5,984 P2P lending platforms from 2007 to 2019. The dependent variable is *Collapse,* a dummy variable that takes the value of one if a P2P platform collapses in a year, and zero otherwise. *DriveDistance* and *DriveTime* are the log values of the driving distance and the driving time between a P2P lending platform and the local financial office. Refer to Appendix A for the detailed definitions of other variables. Constant term is included in all regressions but not tabulated. The *z*-statistics reported in parentheses are based on robust standard errors clustered at platform and year levels. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Y: Collapse	(1)	(2)	(3)	(4)
DriveDistance	**0.108*** **	**0.071*** **		
	(7.12)	**(7.79)**		
DriveTime			**0.169*** **	**0.103*** **
			(6.48)	**(4.80)**
DistanceBank		0.018		0.015
		(1.52)		(1.23)
RegCapital		-0.153***		-0.153***
		(-3.36)		(-3.37)
Collateral		-0.576**		-0.573**
		(-2.28)		(-2.27)
CapitalDeposit		-1.830***		-1.830***
		(-3.52)		(-3.52)
RiskDeposit		0.106		0.110
		(0.56)		(0.58)
GDP/PC		0.066		0.074
		(1.16)		(1.25)
Deposit/GDP		-0.469*		-0.466*
		(-1.80)		(-1.78)
Loan/GDP		-0.020		-0.016
		(-0.08)		(-0.06)
MobilePhone/PC		0.023		0.020
		(0.43)		(0.38)
Province	NO	YES	NO	YES
Year	NO	YES	NO	YES
N	18,044	18,012	18,044	18,012
Pseudo R^2	0.002	0.158	0.003	0.158

Table 4: DID analysis using the relocation of Hangzhou government

This table reports the results of the multivariate DID analysis. Column 1 uses the full sample and Column 2 uses the propensity score matched sample in the [-3 years, + 3 years] around the relocation event, based on the nearest neighbor matching method with a 1:4 treatment to control group ratio. Panel B presents the dynamic DID regression results on the effect of regulatory distance on the collapse rate of P2P platforms. *Collapse* is a dummy variable that takes the value of one if a P2P platform collapses in a year, and zero otherwise. *Treat* is a dummy variable that takes the value of one if a P2P lending platform in Hangzhou is established before the government moved and has a longer straight-line distance before than after the government's relocation and otherwise zero. *Post* is a dummy variable that takes a value of one for the 2017-2019 post-relocation period, and zero otherwise. *After(i)yr* is a dummy variable indicating an observation is i year after the relocation event. *Before(i)yr* is a dummy variable indicating an observation is i year before the relocation event, where i=1, 2 and 3. Refer to Appendix A for the detailed definitions of all the other variables. The z-statistics reported in parentheses are based on robust standard errors clustered at the platform and year level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: DID regression result

	(1)	(2)
Y: Collapse	Full	PSM-DID[-3,3]
Treat×Post	**1.027***	**1.053*****
	(1.67)	**(3.98)**
Treat	-0.435	-0.522**
	(-1.08)	(-2.22)
DistanceBank	0.045***	0.029
	(3.44)	(0.29)
RegCapital	-0.154***	-0.121
	(-3.38)	(-1.28)
Collateral	-0.580**	-0.412
	(-2.29)	(-1.54)
CapitalDeposit	-1.850***	-1.677***
	(-3.59)	(-3.44)
RiskDeposit	0.093	0.105
	(0.50)	(0.47)
GDP/PC	0.052	-1.603
	(0.94)	(-1.29)
Deposit/GDP	-0.485*	-2.711***
	(-1.88)	(-3.70)
Loan/GDP	-0.001	4.007
	(-0.01)	(1.27)
MobilePhone/PC	0.031	-0.286
	(0.56)	(-0.18)
Province	YES	YES
Year	YES	YES
N	1,8012	2,734
Pseudo R^2	0.158	0.183

Panel B: Dynamic analysis using the relocation of the Hangzhou government office

Y: Collapse	(1)	(2)
Treat×Before3yr		0.647
		(1.32)
Treat×Before2yr	0.108	0.172
	(0.28)	(0.39)
Treat×Before1yr	-0.083	-0.028
	(-0.20)	(-0.06)
Treat×After1yr	**0.059**	**0.094**
	(0.19)	**(0.28)**
Treat×After2yr	**0.906****	**0.938****
	(2.28)	**(2.27)**
Treat×After3yr		**1.012****
		(2.20)
DistanceBank	0.015	0.012
	(0.16)	(0.12)
RegCapital	-0.115	-0.114
	(-1.23)	(-1.23)
Collateral	-0.425	-0.449*
	(-1.64)	(-1.67)
CapitalDeposit	-1.709***	-1.716***
	(-3.49)	(-3.48)
RiskDeposit	0.100	0.106
	(0.42)	(0.46)
GDP/PC	-1.472	-1.474
	(-0.88)	(-0.81)
Deposit/GDP	-2.191***	-2.201**
	(-3.32)	(-2.54)
Loan/GDP	3.300	3.161
	(0.93)	(0.80)
MobilePhone/PC	-0.702	-0.662
	(-0.33)	(-0.31)
Province	YES	YES
Year	YES	YES
N	2,736	2,736
Pseudo R^2	0.188	0.188

Table 5: DID analysis: subway station openings

Panel A reports the DID analysis results. Our sample consists of 18,044 platform-year observations, and 5,984 unique P2P lending platforms from 2007 to 2019. Panel B presents the dynamic DID regression results of the collapse rate before and after subway opening. *Collapse* is a dummy variable that takes the value of 1 if a P2P lending platform collapses in that year, and zero otherwise. *Subway_1km* is a dummy variable which takes the value of 1 if the nearest subway station of the P2P lending platform is located within 1km and the P2P lending platform has been established before the opening of the subway; and 0 otherwise. *AfterOpen* is a dummy variable indicating the time period after the opening of the nearest subway station within 1 km of P2P lending platform. Refer to Appendix A for the detailed definitions of all the other variables. The z-statistics reported in parentheses are based on robust standard errors clustered at the platform and year level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: DID regression result

	(1)	(2)	(3)
Y: Collapse	Full	Full[-3,3]	PSM-DID[-3,3]
Subway_1km×AfterOpen	**-0.150****	**-0.247****	**-0.406*****
	(-2.34)	**(-2.57)**	**(-3.14)**
Subway_1km	-0.140***	-0.174**	-0.253***
	(-2.75)	(-2.34)	(-3.55)
DistanceBank	0.043***	-0.025	-0.048
	(3.19)	(-0.91)	(-1.04)
RegCapital	-0.154***	-0.145***	-0.208***
	(-3.40)	(-2.88)	(-3.21)
Collateral	-0.582**	-0.329	-0.389**
	(-2.30)	(-1.60)	(-2.02)
CapitalDeposit	-1.840***	-1.934***	-2.056***
	(-3.53)	(-3.35)	(-3.90)
RiskDeposit	0.092	0.153	0.630**
	(0.48)	(0.61)	(2.34)
GDP/PC	0.086	0.065	0.060
	(1.45)	(0.16)	(0.12)
Deposit/GDP	-0.472*	0.033	-0.674
	(-1.82)	(0.07)	(-0.96)
Loan/GDP	0.016	-0.589	0.717
	(0.06)	(-0.81)	(0.66)
MobilePhone/PC	0.024	-0.131	0.011
	(0.46)	(-0.27)	(0.01)
Province	YES	YES	YES
Year	YES	YES	YES
N	18,012	6,004	7,899
Pseudo R^2	0.158	0.167	0.187

Panel B: The Dynamics of the collapse rate before and after subway opening

Y: Collapse	(1) PSM-DID	(2) PSM-DID
Subway_1km×Before2yr		-0.135
		(-1.06)
Subway_1km×Before1yr	-0.104	-0.120
	(-0.96)	(-1.10)
Subway_1km×After1yr	**-0.389*** **	**-0.409*** **
	(-2.65)	**(-2.76)**
Subway_1km×After2yr		**-0.515*** **
		(-2.87)
DistanceBank	0.016	0.016
	(0.47)	(0.46)
RegCapital	-0.218***	-0.219***
	(-6.85)	(-6.87)
Collateral	-0.639***	-0.641***
	(-3.63)	(-3.63)
CapitalDeposit	-1.933***	-1.932***
	(-20.28)	(-20.27)
RiskDeposit	0.268	0.269
	(1.19)	(1.20)
GDP/PC	-0.001	0.010
	(-0.01)	(0.08)
Deposit/GDP	-0.502	-0.509
	(-1.16)	(-1.18)
Loan/GDP	0.202	0.203
	(0.46)	(0.46)
MobilePhone/PC	0.171*	0.172*
	(1.70)	(1.70)
Province	YES	YES
Year	YES	YES
N	17,683	17,683
Pseudo R^2	0.183	0.183

Table 6: Instrumental variable approach

This table presents the instrumental variable analysis result using IVProbit regressions. Instrumental variable is *Street*, defined as the number of streets that one needs to pass in order to drive to the P2P lending platform. Our sample consists of 18,044 platform-year observations for 5,984 P2P lending platforms from 2007 to 2019. *Collapse* is a dummy variable which takes the value of one if a P2P lending platform collapses in a year, and zero otherwise. *DriveDistance* and *DriveTime* are the log values of the driving distance and the driving time between the P2P lending platform and its local financial office, respectively. *StraightDistance* is the straight-line distance between the local financial office and the P2P lending platform. Refer to Appendix A for the detailed definitions of other variables. The *t or z* statistics reported in parentheses are based on robust standard errors clustered at the platform level. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	(1) *DriveDistance*	(2) *Collapse*	(3) *DriveTime*	(4) *Collapse*
Street	**0.008*****		**0.010*****	
	(10.95)		**(12.88)**	
DriveDistance		**0.850****		
		(2.42)		
DriveTime				**0.654****
				(2.42)
StraightDistance	0.897***	-0.741**	0.645***	-0.401**
	(163.21)	(-2.28)	(107.19)	(-2.17)
DistanceBank	0.005	0.003	0.010***	0.001
	(1.62)	(0.29)	(2.99)	(0.08)
RegCapital	0.001	-0.090***	-0.001	-0.089***
	(0.23)	(-8.61)	(-0.42)	(-8.56)
Collateral	0.016	-0.337***	-0.013	-0.317***
	(1.33)	(-5.87)	(-0.80)	(-5.55)
CapitalDeposit	-0.003	-1.024***	0.001	-1.033***
	(-0.51)	(-31.95)	(0.14)	(-34.02)
RiskDeposit	-0.002	0.062	-0.025	0.077
	(-0.11)	(0.98)	(-1.20)	(1.20)
GDP/PC	-0.030**	0.072*	-0.088***	0.105**
	(-2.28)	(1.76)	(-8.73)	(2.24)
Deposit/GDP	0.070**	-0.307**	0.041	-0.275**
	(2.53)	(-2.52)	(1.15)	(-2.24)
Loan/GDP	-0.020	-0.027	-0.076**	0.005
	(-0.60)	(-0.23)	(-2.17)	(0.04)
MobilePhone/PC	0.007	0.008	0.026***	-0.002
	(0.99)	(0.23)	(3.32)	(-0.07)
Province	YES	YES	YES	YES
Year	YES	YES	YES	YES
N	18,044	18,012	18,044	18,012
Adj-R^2	0.967		0.926	
F	2,964		1,730	
Wald(p_exog)		0.010		0.017

Table 7: Economics mechanisms: information exchange

This table investigates the relationship between regulatory distance and information exchange. Our sample consists of 18,044 platform-year observations of 5,984 P2P lending platforms from 2007 to 2019. *Onsite* is a dummy variable that takes the value of one if a local government leader inspects the P2P lending platform in a year, and zero otherwise. *DriveDistance* and *DriveTime* are the log values of the driving distance and the driving time between the P2P lending platform and the local financial office, respectively. Refer to Appendix A for the detailed definitions of other variables. The z-statistics reported in parentheses are based on robust standard errors clustered at platform and year levels. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	Onsite	*Onsite*	*Collapse*	*Collapse*
DriveDistance	**-0.158***		**0.070*****	
	(-1.75)		**(7.87)**	
DriveTime		**-0.216***		**0.102*****
		(-1.89)		**(4.82)**
Onsite			**-0.921****	**-0.919****
			(-2.28)	**(-2.28)**
DistanceBank	-0.108	-0.108	0.018	0.015
	(-1.30)	(-1.31)	(1.52)	(1.22)
RegCapital	0.180**	0.180**	-0.152***	-0.152***
	(2.10)	(2.10)	(-3.36)	(-3.37)
Collateral	0.306	0.302	-0.577**	-0.573**
	(1.03)	(1.01)	(-2.28)	(-2.28)
CapitalDeposit	1.730***	1.732***	-1.817***	-1.817***
	(9.11)	(9.12)	(-3.51)	(-3.52)
RiskDeposit	0.387	0.385	0.111	0.115
	(1.13)	(1.12)	(0.59)	(0.61)
GDP/PC	0.380	0.362	0.067	0.075
	(1.18)	(1.12)	(1.17)	(1.27)
Deposit/GDP	0.334	0.311	-0.462*	-0.459*
	(0.36)	(0.33)	(-1.79)	(-1.78)
Loan/GDP	-0.458	-0.449	-0.027	-0.023
	(-0.52)	(-0.51)	(-0.10)	(-0.09)
MobilePhone/PC	0.075	0.077	0.025	0.022
	(0.37)	(0.39)	(0.47)	(0.42)
Province	YES	YES	YES	YES
Year	YES	YES	YES	YES
N	17,959	17,959	18,012	18,012
Pseudo R^2	0.113	0.113	0.159	0.159

Table 8: Economics mechanisms: resource constraints

This table investigates the relationship between regulatory distance and resource constraints. Our sample consists of 18,044 platform-year observations, with 5,984 unique P2P lending platforms from 2007 to 2019. *RegExp* is the logarithm of the annual financial regulatory expenditure for each province divided by the total number of platforms in each province. *DriveDistance* and *DriveTime* are the log values of the driving distance and the driving time between a P2P lending platform and the local financial office. Refer to Appendix A for the detailed definitions of other variables. The *z*-statistics reported in parentheses are based on robust standard errors clustered at platform and year levels. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Y: Collapse	(1)	(2)
DriveDistance×RegExp	**-0.195***	
	(-1.77)	
DriveTime×RegExp		**-0.260***
		(-1.80)
DriveDistance	0.097***	
	(6.35)	
DriveTime		0.139***
		(5.21)
RegExp	-0.103	0.191
	(-0.44)	(0.54)
DistanceBank	0.016	0.013
	(1.40)	(1.11)
RegCapital	-0.153***	-0.153***
	(-3.35)	(-3.36)
Collateral	-0.580**	-0.577**
	(-2.29)	(-2.29)
CapitalDeposit	-1.834***	-1.833***
	(-3.54)	(-3.54)
RiskDeposit	0.112	0.113
	(0.59)	(0.60)
GDP/PC	0.064	0.071
	(1.12)	(1.21)
Deposit/GDP	-0.443*	-0.438*
	(-1.76)	(-1.74)
Loan/GDP	-0.029	-0.026
	(-0.11)	(-0.10)
MobilePhone/PC	0.024	0.021
	(0.44)	(0.39)
Province	YES	YES
Year	YES	YES
N	18,012	18,012
Pseudo R^2	0.159	0.159

Table 9: Influence of regulatory discretion: a policy shock in 2016

This table investigates the impact of regulatory distance on the collapse of P2P lending platforms after clarifying the regulatory responsibilities of local financial offices on P2P lending platforms. Our sample consists of 18,044 platform-year observations for 5,984 P2P lending platforms from 2007 to 2019. *Collapse* is a dummy variable that takes the value of one if a P2P lending platform collapses in a year, and zero otherwise. *DriveDistance* and *DriveTime* are the log values of the driving distance and the driving time between a P2P lending platform and a local financial office. *Policy* is a dummy variable indicating the policy period from 2017 to 2019. Refer to Appendix A for the detailed definitions of other variables. The *z*-statistics reported in parentheses are based on robust standard errors clustered at platform and year levels. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Y: Collapse	(1)	(2)
DriveDistance×Policy	**-0.043****	
	(-2.01)	
DriveDistance	0.084***	
	(12.07)	
DriveTime×Policy		**-0.076*****
		(-2.86)
DriveTime		0.126***
		(7.09)
DistanceBank	0.018	0.015
	(1.55)	(1.26)
RegCapital	-0.152***	-0.152***
	(-3.35)	(-3.35)
Collateral	-0.576**	-0.573**
	(-2.27)	(-2.27)
CapitalDeposit	-1.832***	-1.832***
	(-3.52)	(-3.53)
RiskDeposit	0.108	0.111
	(0.57)	(0.59)
GDP/PC	0.065	0.072
	(1.14)	(1.23)
Deposit/GDP	-0.463*	-0.455*
	(-1.75)	(-1.72)
Loan/GDP	-0.026	-0.025
	(-0.10)	(-0.09)
MobilePhone/PC	0.022	0.020
	(0.41)	(0.37)
Province	YES	YES
Year	YES	YES
N	18,012	18,012
Pseudo R^2	0.158	0.159

Table 10: Collapse types and operation time of P2P lending platforms

This table investigates the effect of regulatory distance on P2P lending platforms' collapse types and operation time. Our sample consists of 4,802 collapsed P2P lending platforms from 2011 to 2019. *Benign* is a dummy variable that takes the value of one if the collapsed P2P lending platform has benign exit and zero otherwise. *Fraud* is a dummy variable that takes the value of one if the collapsed P2P lending platform has malicious scam or fraud and zero otherwise. *SurvivalTime* is the log value of the number of days from the platform establishment date to its collapse date. *DriveDistance* and *DriveTime* are the log values of the driving distance and the driving time between a P2P lending platform and a local financial office, respectively. Refer to Appendix A for the detailed definitions of other variables. The t or z statistics reported in parentheses are based on robust standard errors clustered at the platform level. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Benign	*Benign*	*Fraud*	*Fraud*	*SurvivalTime*	*SurvivalTime*
DriveDistance	**-0.169*** **		**0.085** **		**-0.066*** **	
	(-2.92)		**(2.17)**		**(-3.63)**	
DriveTime		**-0.235*** **		**0.079**		**-0.091*** **
		(-3.04)		**(1.54)**		**(-3.82)**
DistanceBank	-0.031	-0.028	0.006	0.017	-0.050***	-0.048***
	(-0.66)	(-0.59)	(0.19)	(0.50)	(-3.18)	(-3.09)
RegCapital	-0.075	-0.075	0.115***	0.115***	-0.113***	-0.113***
	(-1.51)	(-1.52)	(3.64)	(3.63)	(-7.17)	(-7.19)
Collateral	0.117	0.113	-0.084	-0.082	-0.062	-0.064
	(0.47)	(0.45)	(-0.40)	(-0.40)	(-0.98)	(-1.01)
CapitalDeposit	-0.084	-0.082	0.937***	0.932***	0.356***	0.357***
	(-0.48)	(-0.48)	(6.98)	(6.94)	(8.76)	(8.80)
RiskDeposit	0.106	0.104	-0.042	-0.041	0.340***	0.339***
	(0.35)	(0.35)	(-0.19)	(-0.18)	(3.89)	(3.88)
GDP/PC	0.024	0.011	0.102	0.101	-0.008	-0.013
	(0.14)	(0.06)	(1.00)	(0.98)	(-0.17)	(-0.28)
Deposit/GDP	-0.374	-0.402	-0.214	-0.216	0.353**	0.346**
	(-0.76)	(-0.82)	(-0.62)	(-0.63)	(2.38)	(2.33)
Loan/GDP	0.742	0.755	0.164	0.168	-0.203	-0.202
	(1.59)	(1.61)	(0.52)	(0.53)	(-1.49)	(-1.48)
MobilePhone/PC	0.116	0.122	-0.014	-0.010	0.027	0.030
	(1.06)	(1.11)	(-0.15)	(-0.11)	(0.96)	(1.04)
Province	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES
N	4,759	4,759	4,801	4,801	4,802	4,802
Adj-R^2/Pseudo R^2	0.165	0.166	0.092	0.092	0.362	0.362

Internet Appendix for

“Monitoring Fintech Firms: Evidence from The Collapse of Peer-to-Peer Lending Platforms”

This Internet Appendix provides supplemental analyses and robustness tests to the main results presented in “***Monitoring Fintech Firms: Evidence from The Collapse of Peer-to-Peer Lending Platforms***”. This appendix has been provided by the authors to give readers additional information about their research. This document includes:

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Figure IA 1：Timeline of China's P2P Lending Regulatory Policies

The figure lists out policies issued over time for the regulation of the online P2P lending industry, along with the date and issuing agencies, such as the People's Bank of China, China Banking Regulatory Commission, etc.

Time	Issuing Agency	File Name
2015/7/18	The People's Bank of China	Guiding Opinions on Enhancing Positive Development of Internet Finance
	中国人民银行	关于促进互联网金融健康发展的指导意见
2015/12/28	China Banking Regulatory Commission	Interim Measures for the Administration of the Business Activities of Online Lending Information Intermediary Institutions (Exposure draft)
	中国银行业监督管理委员会	网络借贷信息中介机构业务活动管理暂行办法(征求意见稿)
2016/4/12	The General Office of the State Council	Notice on Issuing the Implementation Plan for Special Rectification on Risks in Internet Finance
	国务院办公厅	互联网金融风险专项整治工作实施方案
2016/4/13	China Banking Regulatory Commission	Notice on Issuing the Implementation Plan for Special Rectification on Risks in P2P Lending
	中国银行业监督管理委员会	P2P 网络借贷风险专项整治工作实施方案
2016/8/24	China Banking Regulatory Commission	Interim Measures for the Administration of the Business Activities of Online Lending Information Intermediary Institutions
	中国银行业监督管理委员会	网络借贷信息中介机构业务活动管理暂行办法
2016/11/30	China Banking Regulatory Commission	Guidance of Online Lending Information Intermediary Institutions Recordation Administration
	中国银行业监督管理委员会	网络借贷信息中介机构备案登记管理指引
2017/2/22	China Banking Regulatory Commission	Notice on Issuing the Guidelines for the Online Lending Fund Depository Business
	中国银行业监督管理委员会	网络借贷资金存管业务指引
2017/6/29	The People's Bank of China	Notice on Further Improving the Special Rectification and Rectification of Internet Financial Risks
	中国人民银行	关于进一步做好互联网金融风险专项整治清理整顿工作的通知
2017/6/30	The Office for the Special Campaign against Internet Financial Risks	Notice on Conducting the Clean-up and Rectification in Respect of Internet Platforms and Various Trading Venues Cooperating in Engaging in Business in Violation of Laws and Regulation
	互联网金融风险专项整治工作领导小组办公室	关于对互联网平台与各类交易场所合作从事违法违规业务开展清理整顿的通知
2017/8/24	China Banking Regulatory Commission	Notice on Issuing the Guidelines for the Disclosure of Information on the Business Activities of Online Lending Information Intermediary Institutions
	中国银行业监督管理委员会	网络借贷信息中介机构业务活动信息披露指引
2017/11/21	The Office for the Special Campaign against P2P Lending Risks	Notice on Conducting the Evaluation of Online Loan Fund Depository
	P2P 网络借贷风险专项整治领导小组办公室	关于开展网络借贷资金存管测评工作的通知

2017/12/1	The Office for the Special Campaign against P2P Lending Risks	Notice on Issuing the Regulation and Rectification of the “Cash Loan” Business
	P2P 网络借贷风险专项整治领导小组办公室	关于规范整顿“现金贷”业务的通知
2017/12/8	The Office for the Special Campaign against Peer-to-peer Lending Risks	Implementation Plan for Special Rectification of Risks in Small Loan Companies and Online Small Loan
	P2P 网络借贷风险专项整治领导小组办公室	小额贷款公司网络小额贷款业务风险专项整治实施方案
2018/3/28	The Office for the Special Campaign against Peer-to-peer Lending Risks	Notice on Strengthening the Rectification of Asset Management Business through the Internet and Conducting Acceptance Work
	互联网金融风险专项整治工作领导小组办公室	关于加大通过互联网开展资产管理业务整治力度及开展验收工作的通知
2018/8/13	The Office for the Special Campaign against Peer-to-peer Lending Risks	Notice on Conducting Compliance Inspection of P2P Online Lending Platforms
	P2P 网络借贷风险专项整治领导小组办公室	关于开展 P2P 网络借贷机构合规检查工作的通知
2018/12/19	The Office for the Special Campaign against Peer-to-peer Lending Risks	Opinions on Doing a Good Job in Classifying Disposal and Risk Prevention of Online Lending Institutions
	P2P 网络借贷风险专项整治领导小组办公室	关于做好网贷机构分类处置和风险防范工作的意见
2019/1/24	The Office for the Special Campaign against Peer-to-peer Lending Risks	Notice on Further Strengthening the Compliance Inspection and Follow-up Work of P2P lending
	P2P 网络借贷风险专项整治领导小组办公室	关于进一步做实 P2P 网络借贷合规检查及后续工作的通知
2019/9/25	The Office for the Special Campaign against Peer-to-peer Lending Risks	Notice on Further Strengthening the Depository Work of Online Lending Funds
	P2P 网络借贷风险专项整治领导小组办公室	关于进一步加强网络借贷资金存管工作的通知
2019/11/27	The Office for the Special Campaign against Peer-to-peer Lending Risks	Guiding Opinions on the Pilot Program of Transforming Online Lending Institutions into Small Loan Companies
	P2P 网络借贷风险专项整治领导小组办公室	关于网络借贷信息中介机构转型为小额贷款公司试点的指导意见

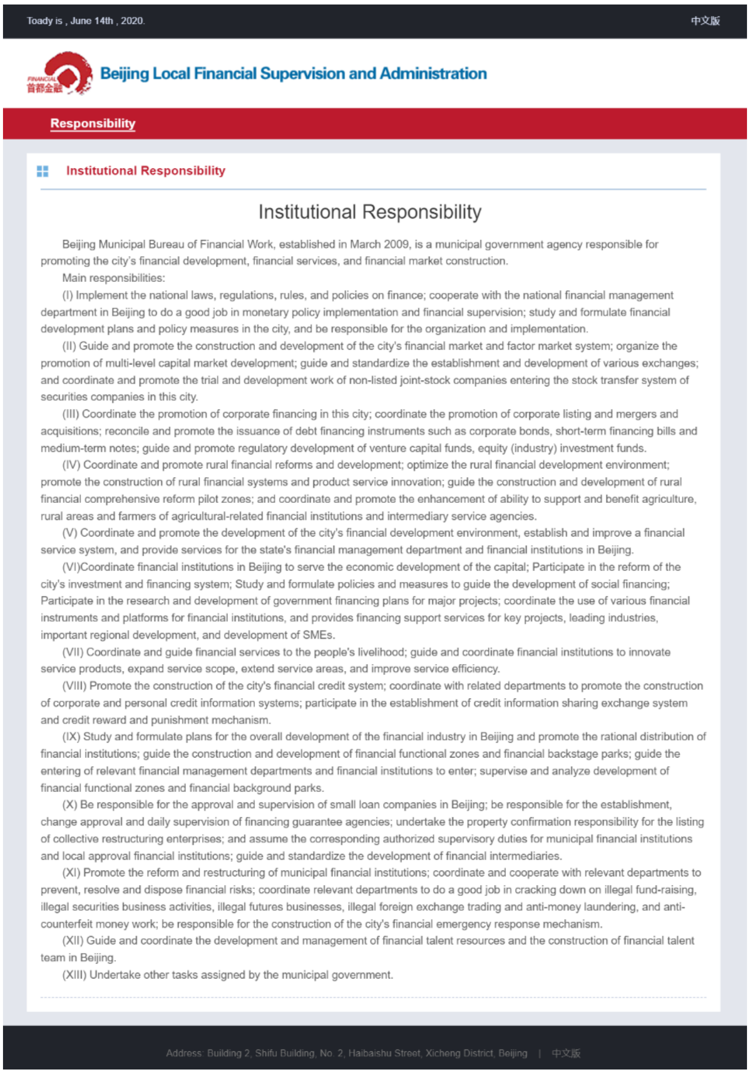
Figure IA 2: Establishment Year of Provincial Financial Office

This table shows the year when the provincial financial office was established for each of the 31 provinces and municipalities in China. This table is in ascending order by the year of establishment of the financial office.

Province	Year	Name of Institution
Heilongjiang	1999	黑龙江省金融工作领导小组办公室
Jilin	1999	吉林省地方金融工作领导小组
Heibei	2001	河北省金融工作办公室
Beijing	2002	北京市金融工作办公室
Liaoning	2002	辽宁省金融办公室
Shanghai	2002	上海市金融服务办公室
Ningxia	2003	宁夏金融管理办公室
Chongqing	2004	重庆市金融工作办公室
Guangdong	2004	广东省金融服务办公室
Guangxi	2004	广西金融工作领导小组办公室
Hubei	2004	湖北省金融管理领导小组
Hainan	2005	海南省金融工作办公室
Jiangsu	2005	江苏省金融工作办公室
Gansu	2006	甘肃省金融工作办公室
Tianjin	2007	天津市金融服务办公室
Anhui	2009	安徽省金融工作办公室
Henan	2009	河南省金融服务办公室
Hunan	2009	湖南省金融工作办公室
Neimenggu	2009	内蒙古金融工作办公室
Shandong	2009	山东省金融工作办公室
Shanxi(northwest)	2009	陕西省金融工作办公室
Yunnan	2009	云南省金融工作办公室
Zhejiang	2009	浙江省金融工作办公室
Jiangxi	2010	江西省金融工作办公室
Xinjiang	2010	新疆金融工作办公室
Fujian	2011	福建省金融工作领导小组
Guizhou	2011	贵州省金融工作办公室
Qinghai	2011	青海省金融工作办公室
Shanxi	2011	山西省金融工作办公室
Sichuan	2011	四川省金融工作办公室
Xizang	2017	西藏金融工作办公室

Figure IA 3-1: Responsibility of Beijing Local Financial Office

The figure shows a snapshot of the website from Beijing Local Financial Office website, retrieved from "http://jrj.beijing.gov.cn/engjgzz/201910/t20191025_452131.html". The figure claims the responsibility of Beijing Local Financial Office clearly.


Toady is , June 14th , 2020.

中文版

Beijing Local Financial Supervision and Administration

Responsibility

Institutional Responsibility

Institutional Responsibility

Beijing Municipal Bureau of Financial Work, established in March 2009, is a municipal government agency responsible for promoting the city's financial development, financial services, and financial market construction.

Main responsibilities:

(I) Implement the national laws, regulations, rules, and policies on finance; cooperate with the national financial management department in Beijing to do a good job in monetary policy implementation and financial supervision; study and formulate financial development plans and policy measures in the city, and be responsible for the organization and implementation.

(II) Guide and promote the construction and development of the city's financial market and factor market system; organize the promotion of multi-level capital market development; guide and standardize the establishment and development of various exchanges; and coordinate and promote the trial and development work of non-listed joint-stock companies entering the stock transfer system of securities companies in this city.

(III) Coordinate the promotion of corporate financing in this city; coordinate the promotion of corporate listing and mergers and acquisitions; reconcile and promote the issuance of debt financing instruments such as corporate bonds, short-term financing bills and medium-term notes; guide and promote regulatory development of venture capital funds, equity (industry) investment funds.

(IV) Coordinate and promote rural financial reforms and development; optimize the rural financial development environment; promote the construction of rural financial systems and product service innovation; guide the construction and development of rural financial comprehensive reform pilot zones; and coordinate and promote the enhancement of ability to support and benefit agriculture, rural areas and farmers of agricultural-related financial institutions and intermediary service agencies.

(V) Coordinate and promote the development of the city's financial development environment, establish and improve a financial service system, and provide services for the state's financial management department and financial institutions in Beijing.

(VI)Coordinate financial institutions in Beijing to serve the economic development of the capital; Participate in the reform of the city's investment and financing system; Study and formulate policies and measures to guide the development of social financing; Participate in the research and development of government financing plans for major projects; coordinate the use of various financial instruments and platforms for financial institutions, and provides financing support services for key projects, leading industries, important regional development, and development of SMEs.

(VII) Coordinate and guide financial services to the people's livelihood; guide and coordinate financial institutions to innovate service products, expand service scope, extend service areas, and improve service efficiency.

(VIII) Promote the construction of the city's financial credit system; coordinate with related departments to promote the construction of corporate and personal credit information systems; participate in the establishment of credit information sharing exchange system and credit reward and punishment mechanism.

(IX) Study and formulate plans for the overall development of the financial industry in Beijing and promote the rational distribution of financial institutions; guide the construction and development of financial functional zones and financial backstage parks; guide the entering of relevant financial management departments and financial institutions to enter; supervise and analyze development of financial functional zones and financial background parks.

(X) Be responsible for the approval and supervision of small loan companies in Beijing; be responsible for the establishment, change approval and daily supervision of financing guarantee agencies; undertake the property confirmation responsibility for the listing of collective restructuring enterprises; and assume the corresponding authorized supervisory duties for municipal financial institutions and local approval financial institutions; guide and standardize the development of financial intermediaries.

(XI) Promote the reform and restructuring of municipal financial institutions; coordinate and cooperate with relevant departments to prevent, resolve and dispose financial risks; coordinate relevant departments to do a good job in cracking down on illegal fund-raising, illegal securities business activities, illegal futures businesses, illegal foreign exchange trading and anti-money laundering, and anti-counterfeit money work; be responsible for the construction of the city's financial emergency response mechanism.

(XII) Guide and coordinate the development and management of financial talent resources and the construction of financial talent team in Beijing.

(XIII) Undertake other tasks assigned by the municipal government.

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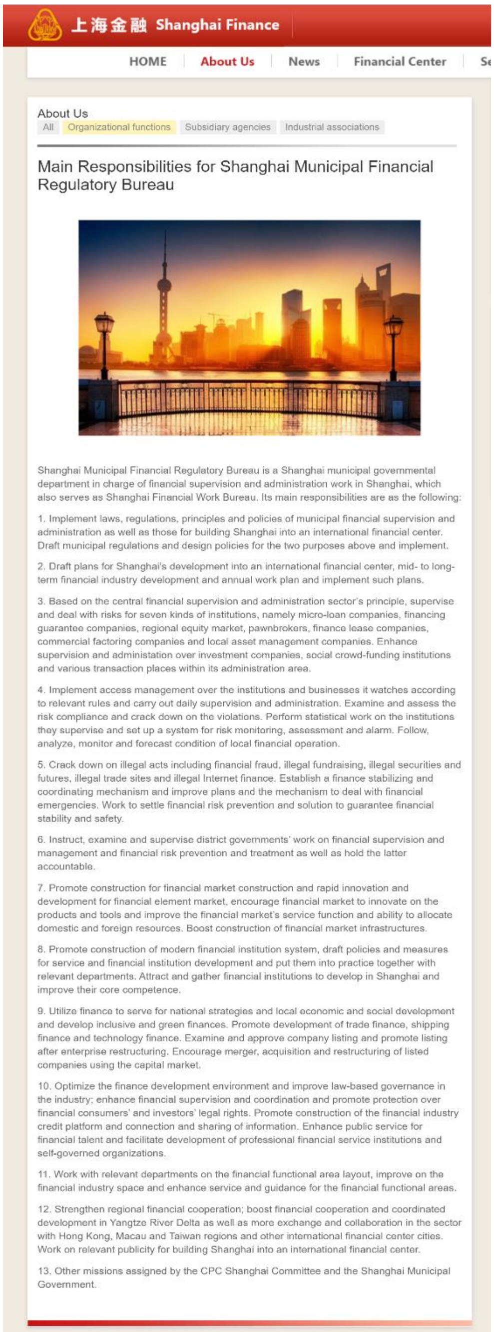
Copy as follows:

(I) Implement the national laws, regulations, rules, and policies on finance; cooperate with the national financial management department in Beijing to do a good job in monetary policy implementation and financial supervision; study and formulate financial development plans and policy measures in the city, and be responsible for the organization and implementation.

(XI) Promote the reform and restructuring of municipal financial institutions; coordinate and cooperate with relevant departments to prevent, resolve and dispose financial risks; coordinate relevant departments to do a good job in cracking down on illegal fund-raising, illegal securities business activities, illegal futures businesses, illegal foreign exchange trading and anti-money laundering, and anti-counterfeit money work; be responsible for the construction of the city's financial emergency response mechanism.

Figure IA 3-2: Responsibility of Shanghai Local Financial Office

The figure is a snapshot of the website from Shanghai Local Financial Office website, retrieved from "http://en.jrj.sh.gov.cn/about-us/organizational-functions/215.shtml". The figure delineates the responsibility of Shanghai Local Financial Office clearly.



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Main Responsibilities for Shanghai Municipal Financial Regulatory Bureau

Shanghai Municipal Financial Regulatory Bureau is a Shanghai municipal governmental department in charge of financial supervision and administration work in Shanghai, which also serves as Shanghai Financial Work Bureau. Its main responsibilities are as the following:

1. Implement laws, regulations, principles and policies of municipal financial supervision and administration as well as those for building Shanghai into an international financial center. Draft municipal regulations and design policies for the two purposes above and implement.

2. Draft plans for Shanghai's development into an international financial center, mid- to long-term financial industry development and annual work plan and implement such plans.

3. Based on the central financial supervision and administration sector's principle, supervise and deal with risks for seven kinds of institutions, namely micro-loan companies, financing guarantee companies, regional equity market, pawnbrokers, finance lease companies, commercial factoring companies and local asset management companies. Enhance supervision and administation over investment companies, social crowd-funding institutions and various transaction places within its administration area.

4. Implement access management over the institutions and businesses it watches according to relevant rules and carry out daily supervision and administration. Examine and assess the risk compliance and crack down on the violations. Perform statistical work on the institutions they supervise and set up a system for risk monitoring, assessment and alarm. Follow, analyze, monitor and forecast condition of local financial operation.

5. Crack down on illegal acts including financial fraud, illegal fundraising, illegal securities and futures, illegal trade sites and illegal Internet finance. Establish a finance stabilizing and coordinating mechanism and improve plans and the mechanism to deal with financial emergencies. Work to settle financial risk prevention and solution to guarantee financial stability and safety.

6. Instruct, examine and supervise district governments' work on financial supervision and management and financial risk prevention and treatment as well as hold the latter accountable.

7. Promote construction for financial market construction and rapid innovation and development for financial element market, encourage financial market to innovate on the products and tools and improve the financial market's service function and ability to allocate domestic and foreign resources. Boost construction of financial market infrastructures.

8. Promote construction of modern financial institution system, draft policies and measures for service and financial institution development and put them into practice together with relevant departments. Attract and gather financial institutions to develop in Shanghai and improve their core competence.

9. Utilize finance to serve for national strategies and local economic and social development and develop inclusive and green finances. Promote development of trade finance, shipping finance and technology finance. Examine and approve company listing and promote listing after enterprise restructuring. Encourage merger, acquisition and restructuring of listed companies using the capital market.

10. Optimize the finance development environment and improve law-based governance in the industry; enhance financial supervision and coordination and promote protection over financial consumers' and investors' legal rights. Promote construction of the financial industry credit platform and connection and sharing of information. Enhance public service for financial talent and facilitate development of professional financial service institutions and self-governed organizations.

11. Work with relevant departments on the financial functional area layout, improve on the financial industry space and enhance service and guidance for the financial functional areas.

12. Strengthen regional financial cooperation; boost financial cooperation and coordinated development in Yangtze River Delta as well as more exchange and collaboration in the sector with Hong Kong, Macau and Taiwan regions and other international financial center cities. Work on relevant publicity for building Shanghai into an international financial center.

13. Other missions assigned by the CPC Shanghai Committee and the Shanghai Municipal Government.

Copy as follows:

1. Implement laws, regulations, principles and policies of municipal financial supervision and administration as well as those for building Shanghai into an international financial center. Draft municipal regulations and design policies for the two purposes above and implement.

5. Crack down on illegal acts including financial fraud, illegal fundraising, illegal securities and futures, illegal trade sites and illegal Internet finance. Establish a finance stabilizing and coordinating mechanism and improve plans and the mechanism to deal with financial emergencies. Work to settle financial risk prevention and solution to guarantee financial stability and safety.

Figure IA 3-3: Performance Appraisal Objectives of Hangzhou Financial Office in 2018

The figure is a snapshot of the website from the People's Government of Zhejiang Province website, retrieved from "http://jrb.hangzhou.gov.cn/art/2018/6/29/art_1228956656_39862056.html". It contains specific objectives of the Hangzhou Financial Office, and "preventing and handling financial risks" is one of the essential goals.

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2018年度杭州市金融办绩效考核目标（指标）公示

发布日期：2018-06-29 访问次数:2 信息来源：杭州市金融办

类别	分项指标	目标名称	考核内容及指标	指标属性	完成时限（月）
绩效指标	职能指标	企业上市	出台《杭州市人民政府关于全面落实"凤凰行动"计划的实施意见》，全年新增上市企业15家。	预期性	12
		金融产业增加值	全市实现金融产业增加值增长8%。	预期性	12
		金融机构存贷款余额	金融机构存贷款余额增速达11.5%。	预期性	12
		不良贷款规模	不良贷款率和关注类贷款规模实现双下降。	预期性	12
		保费收入	保费收入实现正增长。	预期性	12
		非法集资案件控制	非法集资案件高发频发势头得到遏制，新增案件数下降。	预期性	12
工作目标	重点工作目标	钱塘江金融港湾建设	1.出台并实施《加快推进钱塘江金融港湾建设 更好服务实体经济的实施办法（暂定名）》。2.完善钱塘江金融港湾建设项目库，纳入项目库的重点项目不少于50个。3.建立钱塘江金融港湾建设智库。4.举办Money20/20全球金融科技创新博览大会、钱塘江论坛等具有国际影响力的高端论坛峰会。5.完善钱塘江金融港湾信息交流等日常工作机制。6.开建钱塘江金融港湾展示服务中心。	预期性	12
		防范和处置金融风险	1.按照中央及省的部署完成年度全市互联网金融企业的相关整治工作。2.开展全市涉嫌非法集资风险排查工作，排查出的问题整改率100%。3.完成金融风险"天罗地网"监测防控系统建设，严厉打击违法违规金融活动，牢牢守住不发生区域性金融风险底线。4.开展"两链"风险企业情况的监测统计工作。	预期性	12
		优化金融发展环境	1.举办中国金融科技创客大赛（杭州）总决赛。2.举办2018创新中国总决赛暨秋季峰会。3.发布《2017年度杭州股权投资业发展报告》及2018年1-3季度报告。4.加强政金合作，推动市政府与浙商保险、邮储银行浙江省分行续签战略合作协议。	预期性	12
		部门职能兜底考核目标	高质量、高效率完成属于部门"三定"职能范畴或市委市政府交办的其他重要工作，不发生推诿、扯皮等现象。	预期性	12
		重大产业项目招引和推进	按照杭政办函（2018）53号文明确有关部门的招引目标项目以及省市县长工程项目（152工程）的招引和推进个数、项目落地率。（计分方法：1.引进项目个数不低于其目标任务的50%、且最低不少于5个，得70分；引进项目低于目标任务50%的，每低于5个百分点扣2分；虽然不低于目标任务的50%，但省市县长工程项目落地率低于50%的，每低于5个百分点扣2分。2.上一年度引进项目的开工率和项目的成活率、资金到位率、固定资产与研发等软性投入、主营业务营收、税收等项目绩效，占30分（此项今年不涉及）。3.引进所主管产业的产业链引擎性项目，每个加5分；引进的项目被评为"大好高项目"或"小而美项目"，每个分别加10分和5分。重大产业项目招引和推进第1项按照百分制换算，加上第3项，得分在90分以上的，目标考核不扣分，低于90分的，按比例相应扣分。具体由市投资促进领导小组办公室提供依据。）	预期性	12

杭州考评网公示网址：http://220.191.210.153:8023//m2012/allIndic2012.do?id=2602173&year=2018

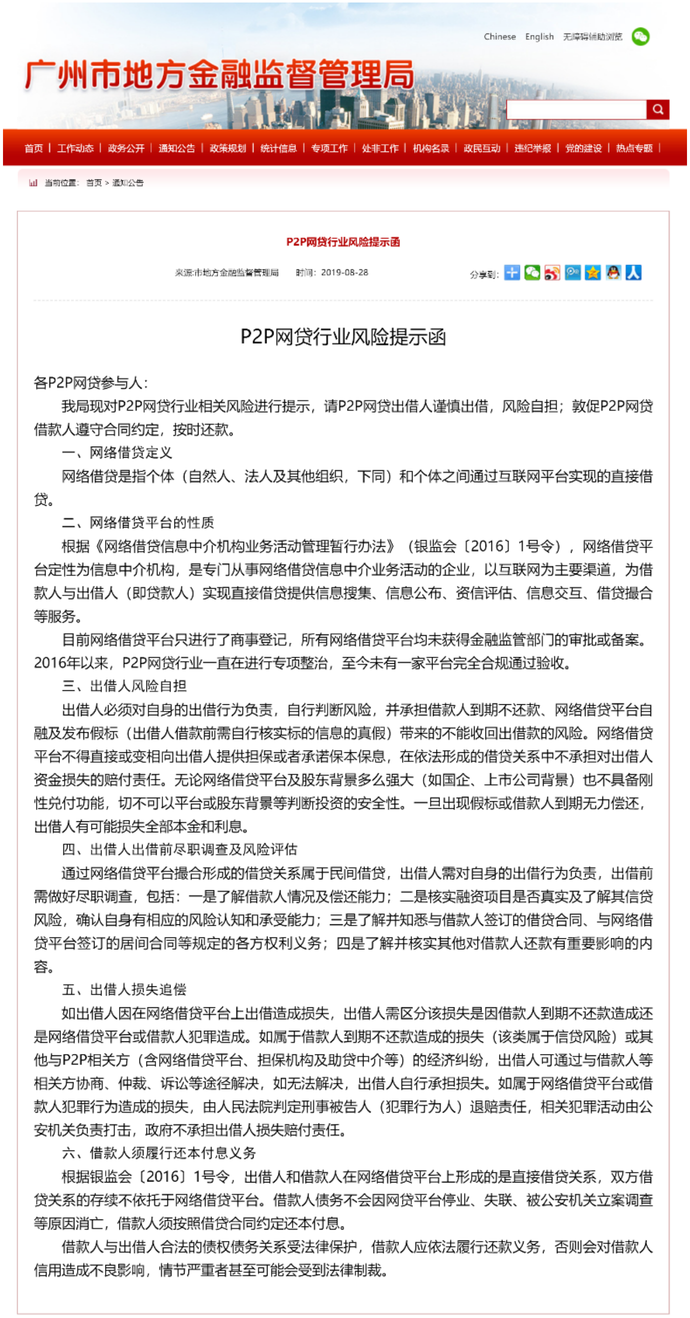
【打印】【关闭】

Figure IA 4-1: One way of Supervision: Onsite Inspection

The figure is a snapshot of the website from Guangzhou Local Financial Supervision and Administration Bureau webside. The address is “http://jrjgj.gz.gov.cn/tzgg/content/post_2789667.html”. It describes the procedures of onsite inspection by Guangzhou Financial Office to monitor P2P lending market.

Figure IA 4-2: One way of Supervision: Risk Reminder

The figure is a snapshot of the website from Guangzhou Local Financial Supervision and Administration Bureau website, retrieved from “http://jrjgj.gz.gov.cn/tzgg/content/post_2789595.html”. It serves as a reminder of the potential risks of the P2P lending market by Guangzhou Financial Office.



Chinese English 无障碍辅助浏览

广州市地方金融监督管理局

首页 | 工作动态 | 政务公开 | 通知公告 | 政策规划 | 统计信息 | 专项工作 | 处非工作 | 机构名录 | 政民互动 | 违纪举报 | 党的建设 | 热点专题 |

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P2P网贷行业风险提示函

来源:市地方金融监督管理局 时间：2019-08-28 分享到：

P2P网贷行业风险提示函

各P2P网贷参与人：

我局现对P2P网贷行业相关风险进行提示，请P2P网贷出借人谨慎出借，风险自担；敦促P2P网贷借款人遵守合同约定，按时还款。

一、网络借贷定义

网络借贷是指个体（自然人、法人及其他组织，下同）和个体之间通过互联网平台实现的直接借贷。

二、网络借贷平台的性质

根据《网络借贷信息中介机构业务活动管理暂行办法》（银监会〔2016〕1号令），网络借贷平台定性为信息中介机构，是专门从事网络借贷信息中介业务活动的企业，以互联网为主要渠道，为借款人与出借人（即贷款人）实现直接借贷提供信息搜集、信息公布、资信评估、信息交互、借贷撮合等服务。

目前网络借贷平台只进行了商事登记，所有网络借贷平台均未获得金融监管部门的审批或备案。2016年以来，P2P网贷行业一直在进行专项整治，至今未有一家平台完全合规通过验收。

三、出借人风险自担

出借人必须对自身的出借行为负责，自行判断风险，并承担借款人到期不还款、网络借贷平台自融及发布假标（出借人借款前需自行核实标的信息的真假）带来的不能收回出借款的风险。网络借贷平台不得直接或变相向出借人提供担保或者承诺保本保息，在依法形成的借贷关系中不承担对出借人资金损失的赔付责任。无论网络借贷平台及股东背景多么强大（如国企、上市公司背景）也不具备刚性兑付功能，切不可以平台或股东背景等判断投资的安全性。一旦出现假标或借款人到期无力偿还，出借人有可能损失全部本金和利息。

四、出借人出借前尽职调查及风险评估

通过网络借贷平台撮合形成的借贷关系属于民间借贷，出借人需对自身的出借行为负责，出借前需做好尽职调查，包括：一是了解借款人情况及偿还能力；二是核实融资项目是否真实及了解其信贷风险，确认自身有相应的风险认知和承受能力；三是了解并知悉与借款人签订的借贷合同、与网络借贷平台签订的居间合同等规定的各方权利义务；四是了解并核实其他对借款人还款有重要影响的内容。

五、出借人损失追偿

如出借人因在网络借贷平台上出借造成损失，出借人需区分该损失是因借款人到期不还款造成还是网络借贷平台或借款人犯罪造成。如属于借款人到期不还款造成的损失（该类属于信贷风险）或其他与P2P相关方（含网络借贷平台、担保机构及助贷中介等）的经济纠纷，出借人可通过与借款人等相关方协商、仲裁、诉讼等途径解决，如无法解决，出借人自行承担损失。如属于网络借贷平台或借款人犯罪行为造成的损失，由人民法院判定刑事被告人（犯罪行为人）退赔责任，相关犯罪活动由公安机关负责打击，政府不承担出借人损失赔付责任。

六、借款人须履行还本付息义务

根据银监会〔2016〕1号令，出借人和借款人在网络借贷平台上形成的是直接借贷关系，双方借贷关系的存续不依托于网络借贷平台。借款人债务不会因网贷平台停业、失联、被公安机关立案调查等原因消亡，借款人须按照借贷合同约定还本付息。

借款人与出借人合法的债权债务关系受法律保护，借款人应依法履行还款义务，否则会对借款人信用造成不良影响，情节严重者甚至可能会受到法律制裁。

Figure IA 5: Data Sources of Driving Distance and Driving Time

The figure is a snapshot of the Baidu Map website. It shows the way of collecting the data sources of driving distance and driving time clearly. The data is obtained from “map.baidu.com”.

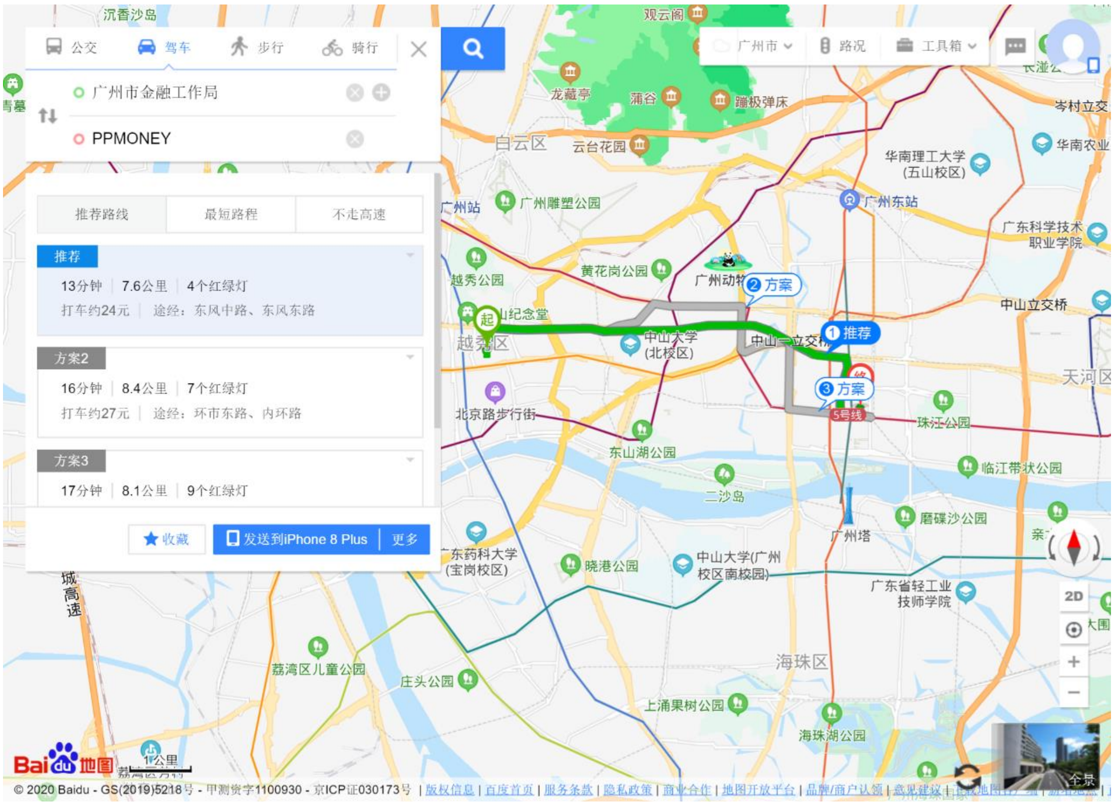

Figure IA 6: Notice on Relocation of Hangzhou Government

The figure is the snapshot of the website from Zhejiang Province Government, retrieved from "http://www.zj.gov.cn/art/2016/10/10/art_37173_285744.html". It announces the relocation of the Hangzhou government to the public.

浙江政务服务网
www.zjzwfw.gov.cn
省级
浙江省政府门户网站
法规政策
当前位置：首页 > 政务公报 > 法规政策 > 政府文件
行政规范性文件

浙江省人民政府关于杭州市人民政府驻地迁移的通知

发布日期：2016-09-30 发布机构：省政府办公厅 文号：浙政发〔2016〕38号

字号：[大 中 小] 打印此页

各市、县（市、区）人民政府，省政府直属各单位：

根据《国务院关于同意浙江省杭州市人民政府驻地迁移的批复》（国函〔2016〕160号）精神，现就有关事项通知如下：

杭州市人民政府驻地由拱墅区环城北路318号迁移至江干区解放东路18号。

此次行政区划调整涉及的经费由杭州市自行解决。要严格执行中央关于厉行节约的规定和国务院"约法三章"的要求，强化组织领导，明确工作责任，加强社会稳定风险评估，落实各项工作措施，确保行政区划调整有序稳妥实施。

浙江省人民政府
2016年9月30日

（此件公开发布）

浙江省人民政府办公厅 2016年9月30日印发

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Figure IA 7: The Straight-Line Distance Between New and Old Government Addresses in Hangzhou
The figure is a snapshot of the Baidu Map website, which illustrates the straight-line distance between the new and old government addresses in Hangzhou. The data is obtained from “map.baidu.com”.

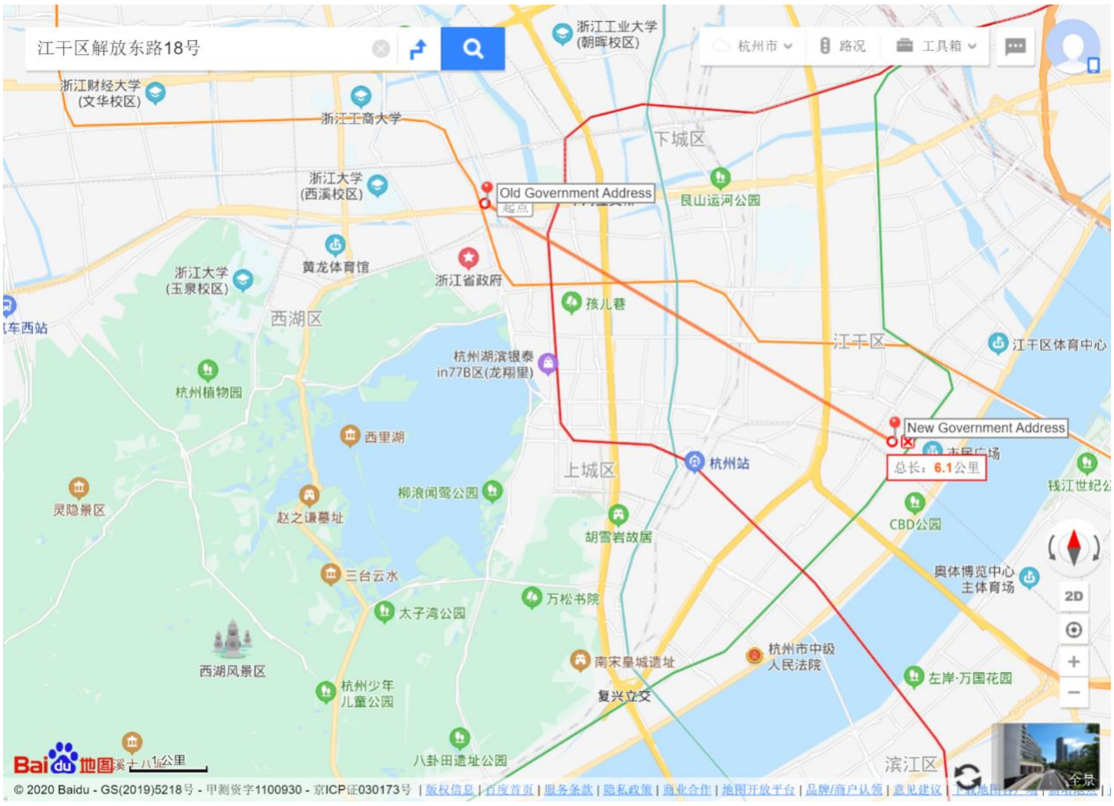

Figure IA 8: An Example of A treated platform: The Relocation of Hangzhou Government Office

Aidai Platform(爱贷网) was established in 2012, the office address is No. 98, Huaxing Road, Xihu District, Hangzhou(杭州市西湖区华星路 98 号). Before the relocation of Hangzhou government in 2016, the straight-line distance between Aidai Platform and the office of the former site of Hangzhou government was 3.6 KM. After the relocation of Hangzhou government in 2016, the straight-line distance between Aidai Platform and the new office of Hangzhou government is 9.7 KM. The relocation of Hangzhou government has increased the distance between Aidai Platform and local financial regulatory authorities. The data is obtained from "map.baidu.com".

Figure IA 9: Parallel Trend Assumption
This figure plots the collapse rate before and after Hangzhou government relocation in 2016. The solid line shows the collapse rate of P2P platforms in the treatment group and the dashed line shows the collapse rate of the control group.

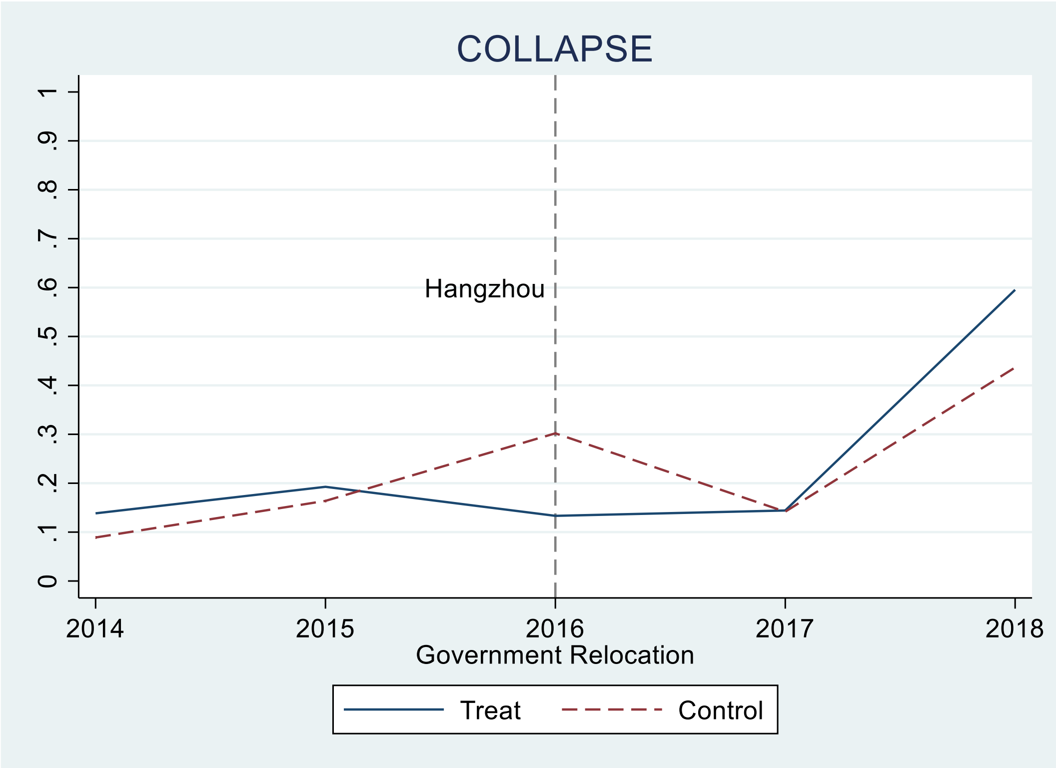

Figure IA 10: Density Distribution of Placebo Test Regression Coefficient

The figure shows the probability density distribution of interaction coefficients in 5,000 estimates. The dots are interaction coefficients of each estimation based on Column (3) in Table 3. The solid line is the probability density distribution based on dots. The dashed line is the mean value of interaction coefficients of the 5,000 runs.

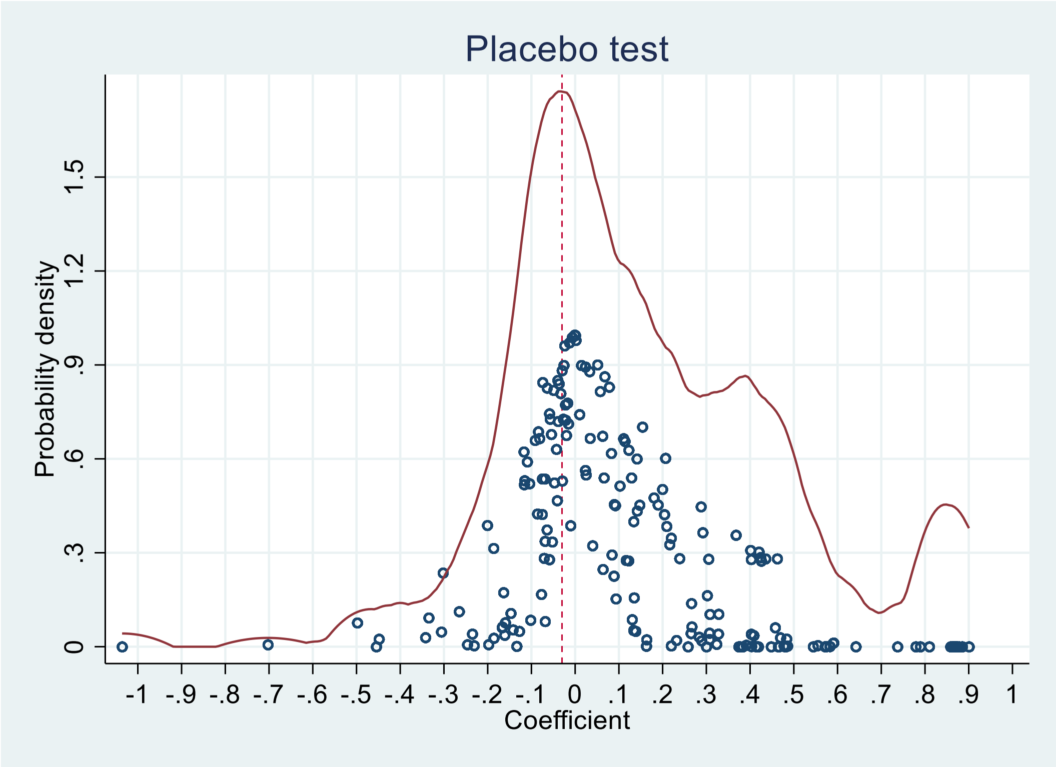

Figure IA 11: An Example of A treated platform: Subway Opening

Honglingchuangtou platform (红岭创投 in Chinese) was established in 2009. Based on baidu map, the nearest subway station to the office of Honglingchuangtou platform is Yitian station (益田站), with a straight-line distance of 830 meters. Yitian station is on Shenzhen Metro Line 3, which started operation in 2010. In this case, the Honglingchuangtou platform is considered as a treat in traffic conditions.

Figure IA 12: Parallel Trend Assumption (Subway Opening)

The figure compares the collapse rate of P2P lending platforms that have new subways opened within 1 km in the current period and do not have any subway in before that. The figure shows the effect of the new opening nearest subway station on the collapse rate of platforms. The year when the new subway station is opened is set as event year. The solid line represents the group that has subway stations and the dashed line represents the group that does not have subways in the past and has newly opened stations.

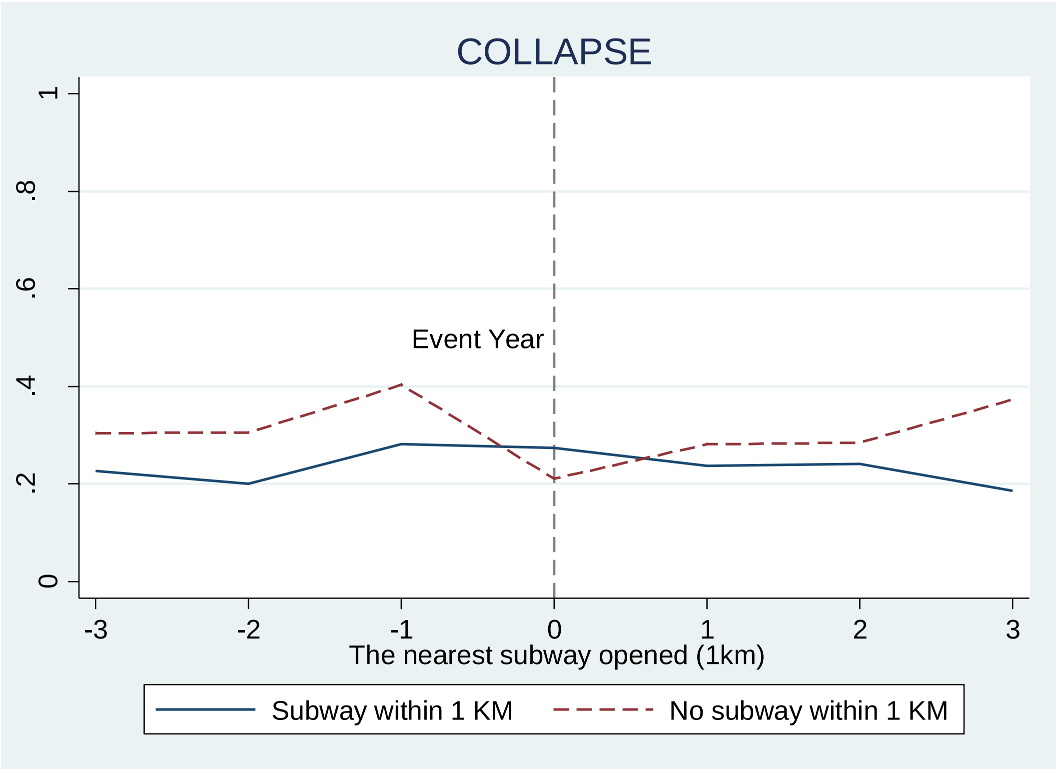

Figure IA 13: Two Cases of Inspections by Local Government Leaders

Case 1: Leaders of Guangzhou Finance Bureau Visited “PPmoney” Platform

广州市金融工作局赴PPmoney网贷考察指导工作

2018-11-30 23:32:04 来源: AI财经观察 举报

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分享至

11月30日，广州市金融工作局地方处欧峻青处长、区喆健副处长、地方金融发展处科长陈龙一行莅临PPmoney万惠集团总部考察，听取PPmoney万惠集团董事长陈宝国、PPmoney网贷CEO胡新汇报公司在合规、运营、风控、技术等方面的发展情况。

当天，个别自媒体在网络上发布关于PPmoney万惠集团的不实信息，广州市金融局领导高度重视该舆情，第一时间委派欧峻青处长一行前往PPmoney万惠集团进行走访调研。公司现场运行一切正常。

Source: https://www.163.com/dy/article/E1T8BC200519WF2E.html

Case 2: The Mayor of Wuxi and the Director of the Municipal Financial Office Visited “KaiXin” Platform

「领导视察」无锡市汪泉市长一行莅临开鑫贷指导工作

摘要：6月1日，无锡市人民政府汪泉市长一行莅临开鑫贷指导工作，市政府副秘书长兼金融办主任王维陪同。开鑫贷周治翰总经理、鲍建富副总经理向汪泉市长一行详细汇报了开鑫贷经营状况、业务创新、风控体系建设等方面的情况。

Source: https://www.kxjf.com/cms/index/dynamic/1719.html

Table IA 1: Covariate Balance Test of The Hangzhou Government Relocation

The table shows the mean test between the treatment and control groups in the covariates. Panel A reports the mean value of variables in the control and treatment groups, where variables are from all of the samples before and after the event. Panel B reports the mean value of variables in the control and treatment groups, where variables are only from the samples before the event. Refer to Appendix A for the detailed definitions of all the other variables. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Covariate balance after PSM

	Treat=0		*Treat=1*		
Variables	N	Mean	N	Mean	Diff.
DistanceBank	2,220	2.115	555	2.121	-0.006
RegCapital	2,220	5.866	555	5.907	-0.042
Collateral	2,220	0.058	555	0.074	-0.016
CapitalDeposit	2,220	0.419	555	0.468	-0.049**
RiskDeposit	2,220	0.036	555	0.032	0.004
GDP/PC	2,220	11.951	555	12.032	-0.080***
Deposit/GDP	2,220	1.103	555	1.136	-0.032***
Loan/GDP	2,220	0.917	555	0.914	0.003
MobilePhone/PC	2,220	1.039	555	1.103	-0.064***

Panel B: Covariate balance after PSM (Before event year 2016)

	Treat=0		*Treat=1*		
Variables	N	Mean	N	Mean	Diff.
DistanceBank	900	2.240	206	2.127	0.114
RegCapital	900	5.784	206	5.631	0.153
Collateral	900	0.046	206	0.049	-0.003
CapitalDeposit	900	0.352	206	0.330	0.022
RiskDeposit	900	0.039	206	0.029	0.010
GDP/PC	900	11.944	206	11.960	-0.016
Deposit/GDP	900	1.113	206	1.091	0.0220
Loan/GDP	900	0.838	206	0.871	-0.033**
MobilePhone/PC	900	1.046	206	1.152	-0.106***

Table IA 2: Placebo Test: Platform Closer to the Government as the Treatment Group

Table IA 2 reports the results of the placebo tests for DID analysis and takes the platforms closer to the government as the treatment group. *Collapse* is a dummy variable which takes the value of one if the observation collapses, and zero otherwise. *MoveNear* are those are established before the government moved and are closer to the financial office after the government moved than before. *Post* is a dummy variable that takes a value of one for the 2017-2019 period, which is the post-period of the government relocation, and zero for the 2009-2016 period. Refer to Appendix A for the detailed definitions of all the other variables. The z-statistics reported in parentheses are based on robust standard errors clustered at the platform and year level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(3)
Y: Collapse	Full	PSM-DID[-3,3]
MoveNear×Post	**0.719**	**0.132**
	(1.26)	**(0.50)**
MoveNear	-0.396	-0.054
	(-1.39)	(-0.15)
DistanceBank	0.045***	-0.051
	(3.41)	(-0.42)
RegCapital	-0.153***	-0.173
	(-3.37)	(-1.42)
Collateral	-0.577**	0.104
	(-2.27)	(0.31)
CapitalDeposit	-1.842***	-1.537**
	(-3.54)	(-2.52)
RiskDeposit	0.097	0.018
	(0.51)	(0.03)
GDP/PC	0.054	-1.146
	(0.95)	(-0.61)
Deposit/GDP	-0.451*	-3.191
	(-1.74)	(-1.31)
Loan/GDP	-0.028	5.783**
	(-0.11)	(2.33)
MobilePhone/PC	0.028	-3.164***
	(0.52)	(-2.66)
Province	YES	YES
Year	YES	YES
N	18,012	1,683
Pseudo R^2	0.158	0.196

Table IA 3: Placebo Test: A City (not Hangzhou) was Randomly Selected as the Treatment Group with 5,000 repetitions

In this table, we present the distribution of the coefficients and *p*-value of *Treat×Post* from DID regressions by reporting the mean, 5th percentile, 25th percentile, median, 75th percentile, 95th percentile.

Y: Collapse	*Treat×Post*						
	Actual	Pseudo					
		Mean	P5	P25	Median	P75	P95
Coefficient	**1.027**	0.154	-0.265	-0.057	0.093	0.374	0.863
P-value	**0.095**	0.316	0.000	0.008	0.278	0.563	0.882

Table IA 4: Covariate Balance: Subway Opening

The table shows the univariate test statistics of key variables including regulatory distance and platform characteristics between the treatment group and the control group. *Subway_1km* is a dummy variable denoting if the nearest subway station of the P2P lending platform is located within 1km and the P2P lending platform has been established before the opening of the subway. The column *Subway_1km=0* indicates observations in the control group. The column *Subway_1km=1* indicates the observations in the treatment group. Refer to Appendix A for the detailed definitions of all the other variables. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Subway_1km=0		*Subway_1km=1*		
Variables	N	Mean	N	Mean	Diff.
DistanceBank	14,276	1.904	3,569	1.895	0.009
RegCapital	14,276	5.652	3,569	5.660	-0.008
Collateral	14,276	0.057	3,569	0.050	0.007
CapitalDeposit	14,276	0.286	3,569	0.299	-0.013
RiskDeposit	14,276	0.027	3,569	0.0250	0.002
GDP/PC	14,276	12.076	3,569	12.080	-0.004
Deposit/GDP	14,276	0.982	3,569	0.981	0.002
Loan/GDP	14,276	0.717	3,569	0.728	-0.012**
MobilePhone/PC	14,276	1.256	3,569	1.249	0.007

Table IA 5: Placebo Test: Subway Opening Range of Treatment Group was 1-2 km, 2-3 km and 3-4 km Respectively

The table reports the Placebo test regression results of new subway station opening events. *Collapse* is a dummy variable which takes the value of one if the observation collapses, and zero otherwise. *Subway1_2km* is the nearest subway station around the P2P lending platform within a linear distance of 1-2 kilometers. *Subway2_3km* is the nearest subway station around the P2P lending platform within a linear distance of 2-3 kilometers. *Subway3_4km* is the nearest subway station around the P2P lending platform within a linear distance of 3-4 kilometers. *AfterOpen* is a dummy variable that the time when the nearest subway station of P2P lending platform was opened. It equal one after the subway station is opened, and otherwise zero. Refer to Appendix A for the detailed definitions of all the other variables. The z-statistics reported in parentheses are based on robust standard errors clustered at the platform and year level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(2)	(1)	(3)
Y: Collapse	Full[-3,3]	Full[-3,3]	Full[-3,3]
Subway1_2km×AfterOpen	**-0.150**		
	(-1.11)		
Subway1_2km	0.035		
	(0.19)		
Subway2_3km×AfterOpen		**-0.182**	
		(-0.57)	
Subway2_3km		0.089	
		(0.58)	
Subway3_4km×AfterOpen			**-0.646**
			(-1.10)
Subway3_4km			0.457**
			(2.26)
DistanceBank	-0.004	-0.006	-0.010
	(-0.18)	(-0.23)	(-0.39)
RegCapital	-0.143***	-0.143***	-0.143***
	(-2.86)	(-2.85)	(-2.85)
Collateral	-0.327	-0.325	-0.329
	(-1.57)	(-1.54)	(-1.55)
CapitalDeposit	-1.942***	-1.946***	-1.947***
	(-3.39)	(-3.41)	(-3.38)
RiskDeposit	0.176	0.175	0.164
	(0.72)	(0.73)	(0.66)
GDP/PC	-0.043	-0.038	-0.027
	(-0.10)	(-0.08)	(-0.06)
Deposit/GDP	0.018	0.014	-0.003
	(0.03)	(0.03)	(-0.01)
Loan/GDP	-0.613	-0.614	-0.594
	(-0.78)	(-0.81)	(-0.75)
MobilePhone/PC	-0.095	-0.104	-0.099
	(-0.19)	(-0.21)	(-0.20)
Province	YES	YES	YES
Year	YES	YES	YES
N	6,004	6,004	6,004
Pseudo R^2	0.165	0.165	0.166

Table IA 6: Placebo Test: A Year was Randomly Selected as the Event Year, and the Regression was 5,000 Times

In this table, we summarize the distribution of the coefficients and *p*-value of *Subway_1km×AfterOpen* from the Time-varying DID regressions by reporting the mean, 5th percentile, 25th percentile, median, 75th percentile, 95th percentile.

Y: Collapse	*Subway_1km×AfterOpen*						
	Actual	Pseudo					
		Mean	P5	P25	Median	P75	P95
Coefficient	**-0.247**	-0.011	-0.041	-0.023	-0.011	0.001	0.019
P-value	**0.010**	0.441	0.014	0.158	0.423	0.709	0.935

Table IA 7: Robustness Test: Change the Independent Variable

In this table, we control the altitude of the terrain differences and use latitude and longitude to calculate the straight-line distance. *Collapse* is a dummy variable which takes the value of one if the observation collapses, and zero otherwise. *StraightDistance* is the straight-line distance between the local financial office and the P2P lending platform. *Altitude* is the altitude of the city where the P2P platform is located, measured as the height above sea level. *Ave_DriveDistance* and *Ave_DriveTime* are the average value of the driving distance and driving time from the local financial office to P2P lending platform and from the P2P lending platform to the local financial office. *Relative_DriveDistance* and *Relative_DriveTime* are relative driving time and relative driving distance, which calculated by dividing *DriveDistance* and *DriveTime* by the logarithm (*lnarea*) of the area of the city. Refer to Appendix A for the detailed definitions of all the other variables. Robust standard errors are clustered at the platform and year level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Y: Collapse	(1)	(2)	(3)	(4)	(5)
StraightDistance	**0.075*** **				
	(7.22)				
Altitude	**-0.000**				
	(-0.03)				
Ave_DriveDistance		**0.076*** **			
		(7.76)			
Ave_DriveTime			**0.107*** **		
			(5.11)		
Relative_DriveDistance				**0.600*** **	
				(8.10)	
Relative_DriveTime					**0.855*** **
					(5.17)
DistanceBank	0.014	0.014	0.014	0.020*	0.018
	(1.06)	(1.17)	(1.08)	(1.78)	(1.55)
RegCapital	-0.153***	-0.153***	-0.153***	-0.153***	-0.153***
	(-3.41)	(-3.45)	(-3.46)	(-3.45)	(-3.46)
Collateral	-0.577**	-0.578**	-0.575**	-0.578**	-0.575**
	(-2.30)	(-2.30)	(-2.30)	(-2.30)	(-2.30)
CapitalDeposit	-1.829***	-1.830***	-1.831***	-1.829***	-1.828***
	(-3.56)	(-3.56)	(-3.57)	(-3.56)	(-3.56)
RiskDeposit	0.110	0.109	0.112	0.108	0.110
	(0.60)	(0.61)	(0.62)	(0.60)	(0.61)
GDP/PC	0.073	0.076	0.080	0.065	0.066
	(1.32)	(1.42)	(1.46)	(1.22)	(1.24)
Deposit/GDP	-0.400	-0.394	-0.392	-0.413*	-0.415*
	(-1.63)	(-1.63)	(-1.62)	(-1.69)	(-1.69)
Loan/GDP	-0.071	-0.079	-0.078	-0.063	-0.056
	(-0.27)	(-0.29)	(-0.28)	(-0.23)	(-0.20)
MobilePhone/PC	0.028	0.029	0.026	0.028	0.024
	(0.50)	(0.51)	(0.47)	(0.49)	(0.42)
Province	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES
N	18,012	18,012	18,012	18,012	18,012
Pseudo R^2	0.158	0.158	0.158	0.158	0.158

Table IA 8: Robustness Test: Using COX and OLS Estimation Method

In this table, we use Cox proportional hazards model and OLS for estimation. *COLLAPSE* is a dummy variable which takes the value of one if the observation collapses, and zero otherwise. *DriveDistance* and *DriveTime* are the log of the driving distance and the driving time between P2P lending platform and local financial office. Refer to Appendix A for the detailed definitions of all the other variables. Robust standard errors are clustered at the platform (and year) level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Y: Collapse	Cox	Cox	OLS	OLS
DriveDistance	**0.042*** **		**0.013*** **	
	(3.10)		**(5.24)**	
DriveTime		**0.062*** **		**0.019*** **
		(3.42)		**(3.83)**
DistanceBank	0.012	0.009	0.002	0.002
	(0.96)	(0.78)	(1.29)	(1.10)
RegCapital	-0.094***	-0.094***	-0.023**	-0.023**
	(-8.91)	(-8.90)	(-2.93)	(-2.94)
Collateral	-0.385***	-0.383***	-0.074***	-0.074***
	(-5.56)	(-5.54)	(-3.19)	(-3.19)
CapitalDeposit	-1.340***	-1.340***	-0.246***	-0.246***
	(-32.17)	(-32.17)	(-4.43)	(-4.43)
RiskDeposit	0.057	0.059	0.017	0.017
	(0.79)	(0.82)	(0.56)	(0.58)
GDP/PC	0.036	0.041	0.010	0.011
	(0.98)	(1.11)	(0.87)	(0.97)
Deposit/GDP	-0.281**	-0.278**	-0.120**	-0.120**
	(-2.31)	(-2.29)	(-2.55)	(-2.55)
Loan/GDP	-0.011	-0.009	0.023	0.024
	(-0.10)	(-0.08)	(0.49)	(0.51)
MobilePhone/PC	0.008	0.006	0.006	0.005
	(0.27)	(0.21)	(0.55)	(0.51)
Province	YES	YES	YES	YES
Year	YES	YES	YES	YES
N	18,044	18,044	18,044	18,044
Adj-R^2			0.156	0.156

Table IA 9-1: Robustness Test: Excluding Samples from Guangdong, Beijing, and Shanghai

Collapse is a dummy variable which takes the value of one if the observation collapses, and zero otherwise. *DriveDistance* and *DriveTime* are the log of the driving distance and the driving time between P2P lending platform and local financial office. Refer to Appendix A for the detailed definitions of all the other variables. The z-statistics reported in parentheses are based on robust standard errors clustered at the platform and year level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Y: Collapse	(1)	(2)	(3)	(4)
DriveDistance	**0.082*** **	**0.062***		
	(3.32)	**(1.80)**		
DriveTime			**0.111*** **	**0.086***
			(2.74)	**(1.70)**
DistanceBank	0.009	-0.007	0.009	-0.008
	(0.50)	(-0.36)	(0.45)	(-0.38)
RegCapital	-0.141***	-0.176***	-0.141***	-0.176***
	(-3.01)	(-3.33)	(-3.02)	(-3.35)
Collateral	-0.408	-0.401	-0.403	-0.395
	(-1.60)	(-1.55)	(-1.59)	(-1.54)
CapitalDeposit	-1.769***	-1.782***	-1.769***	-1.782***
	(-3.49)	(-3.27)	(-3.50)	(-3.27)
RiskDeposit	0.153	0.121	0.155	0.125
	(0.84)	(0.59)	(0.86)	(0.61)
GDP/PC	0.021	0.007	0.025	0.010
	(0.24)	(0.07)	(0.28)	(0.11)
Deposit/GDP	-0.519**	-0.364	-0.520**	-0.365
	(-2.18)	(-1.27)	(-2.20)	(-1.28)
Loan/GDP	-0.009	-0.071	-0.000	-0.065
	(-0.03)	(-0.27)	(-0.00)	(-0.25)
MobilePhone/PC	0.009	0.008	0.006	0.005
	(0.16)	(0.13)	(0.10)	(0.09)
Province	YES	YES	YES	YES
Year	YES	YES	YES	YES
N	14,660	9,512	14,660	9,512
Pseudo R^2	0.156	0.151	0.156	0.151

Table IA 9-2: Robustness Test: Subsample Analysis Before and After 2015

Collapse is a dummy variable which takes the value of one if the observation collapses, and zero otherwise. *DriveDistance* and *DriveTime* are the log of the driving distance and the driving time between P2P lending platform and local financial office. Refer to Appendix A for the detailed definitions of all the other variables. The z-statistics reported in parentheses are based on robust standard errors clustered at the platform and year level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Y: Collapse	Sample period: from 2007 to 2015		Sample period: from 2016 to 2019	
DriveDistance	**0.065*** **	**0.070*** **		
	(4.26)	**(4.82)**		
DriveTime			**0.098** **	**0.099*** **
			(2.20)	**(4.02)**
DistanceBank	0.033**	0.006	0.028	0.005
	(2.17)	(0.29)	(1.26)	(0.24)
RegCapital	-0.241***	-0.075	-0.240***	-0.075
	(-23.31)	(-1.18)	(-23.27)	(-1.19)
Collateral	-1.852***	-0.428*	-1.846***	-0.425*
	(-13.85)	(-1.75)	(-13.44)	(-1.75)
CapitalDeposit	-3.138***	-1.715***	-3.137***	-1.715***
	(-16.65)	(-2.80)	(-16.82)	(-2.80)
RiskDeposit	-0.416	0.399***	-0.412	0.402***
	(-1.48)	(3.14)	(-1.46)	(3.14)
GDP/PC	0.053	0.041	0.059	0.049
	(0.61)	(0.92)	(0.64)	(1.11)
Deposit/GDP	-0.974***	-0.029	-0.973***	-0.024
	(-6.46)	(-0.10)	(-6.41)	(-0.08)
Loan/GDP	0.523***	-0.372	0.530***	-0.369
	(2.77)	(-1.40)	(2.76)	(-1.40)
MobilePhone/PC	0.084*	-0.006	0.081	-0.008
	(1.69)	(-0.10)	(1.58)	(-0.14)
Province	YES	YES	YES	YES
Year	YES	YES	YES	YES
N	7,574	10,438	7,574	10,438
Pseudo R^2	0.161	0.161	0.149	0.149

Table IA 10: Robustness Test: Other Regulatory Bodies

Collapse is a dummy variable which takes the value of one if the observation collapses, and zero otherwise. *CongressDriveDistance* and *CongressDriveTime* are the driving distance and driving time between the People's Congress and P2P lending platform. *CppccDriveDistance* and *CppccDriveTime* are the driving distance and driving time between the Chinese People's Political Consultative Conference and the P2P lending platform. *DriveDistance* and *DriveTime* are the log of the driving distance and the driving time between P2P lending platform and local financial office. Refer to Appendix A for the detailed definitions of all the other variables. The z-statistics reported in parentheses are based on robust standard errors clustered at the platform and year level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Y: Collapse	(1)	(2)	(3)	(4)	(5)	(6)
CongressDriveDistance	**0.051**				**0.023**	
	(1.37)				**(0.52)**	
CongressDriveTime		**0.053**				**-0.005**
		(1.20)				**(-0.09)**
CppccDriveDistance			**0.053**		**0.034**	
			(1.52)		**(0.91)**	
CppccDriveTime				**0.069**		**0.073**
				(1.57)		**(1.42)**
DriveDistance	**0.051*** **		**0.051*** **		**0.049*** **	
	(6.94)		**(7.10)**		**(6.37)**	
DriveTime		**0.084*** **		**0.077*** **		**0.077*** **
		(6.60)		**(5.31)**		**(5.75)**
DistanceBank	-0.000	0.003	0.001	0.003	-0.001	0.003
	(-0.01)	(0.23)	(0.09)	(0.18)	(-0.06)	(0.21)
RegCapital	-0.152***	-0.152***	-0.152***	-0.152***	-0.152***	-0.152***
	(-3.37)	(-3.39)	(-3.36)	(-3.38)	(-3.37)	(-3.39)
Collateral	-0.573**	-0.572**	-0.573**	-0.570**	-0.573**	-0.570**
	(-2.28)	(-2.28)	(-2.28)	(-2.28)	(-2.28)	(-2.28)
CapitalDeposit	-1.829***	-1.831***	-1.828***	-1.830***	-1.828***	-1.830***
	(-3.52)	(-3.52)	(-3.52)	(-3.52)	(-3.52)	(-3.52)
RiskDeposit	0.110	0.113	0.109	0.114	0.110	0.114
	(0.57)	(0.59)	(0.57)	(0.60)	(0.58)	(0.60)
GDP/PC	0.061	0.068	0.062	0.067	0.061	0.068
	(1.07)	(1.15)	(1.07)	(1.13)	(1.07)	(1.15)
Deposit/GDP	-0.462*	-0.465*	-0.456*	-0.457*	-0.458*	-0.457*
	(-1.78)	(-1.78)	(-1.76)	(-1.77)	(-1.76)	(-1.76)
Loan/GDP	-0.030	-0.029	-0.038	-0.038	-0.036	-0.038
	(-0.12)	(-0.11)	(-0.15)	(-0.15)	(-0.14)	(-0.15)
MobilePhone/PC	0.022	0.021	0.022	0.022	0.022	0.022
	(0.41)	(0.40)	(0.42)	(0.42)	(0.41)	(0.42)
Province	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES
N	18,012	18,012	18,012	18,012	18,012	18,012
Pseudo R^2	0.158	0.159	0.158	0.159	0.158	0.159

Table IA 11: Robustness Test: Further Control of Location Factors

Collapse is a dummy variable which takes the value of one if the observation collapses, and zero otherwise. *DriveDistance* and *DriveTime* are the log of the driving distance and the driving time between P2P lending platform and local financial office. *NearestCoffeeShop* is the straight-line distance between the P2P lending platform and the nearest coffee shop. *NearestBar* is the straight-line distance between the P2P lending platform and the nearest bar. *NearestPedestrianmall* is the straight-line distance between the P2P lending platform and the nearest commercial pedestrian street. Refer to Appendix 1 for the detailed definitions of all the other variables. The z-statistics reported in parentheses are based on robust standard errors clustered at the platform and year level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Y: Collapse	(1)	(2)
DriveDistance	0.056***	
	(6.66)	
DriveTime		0.084***
		(4.17)
NearestCoffeeShop	0.066*	0.065*
	(1.89)	(1.88)
NearestBar	-0.009	-0.009
	(-0.59)	(-0.58)
NearestPedestrianmall	-0.008	-0.007
	(-0.38)	(-0.37)
DistanceBank	0.005	0.002
	(0.50)	(0.22)
RegCapital	-0.151***	-0.151***
	(-3.38)	(-3.38)
Collateral	-0.561**	-0.559**
	(-2.29)	(-2.29)
CapitalDeposit	-1.815***	-1.815***
	(-3.50)	(-3.50)
RiskDeposit	0.102	0.105
	(0.53)	(0.55)
GDP/PC	0.106*	0.112*
	(1.83)	(1.89)
Deposit/GDP	-0.456*	-0.454*
	(-1.80)	(-1.79)
Loan/GDP	0.008	0.012
	(0.03)	(0.04)
MobilePhone/PC	0.022	0.019
	(0.40)	(0.36)
Province	YES	YES
Year	YES	YES
N	18,012	18,012
Pseudo R^2	0.159	0.159