Nexus between Commercial Banks and Lending Marketplaces in China

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Table of Contents

List of Figures ..... **iv**

List of Tables ..... **v**

Abstract **1**

1. Overall Introduction **3**

2. Literature Review **9**

2.1 Overview of the Banking Sector 9

2.1.1 The Banking Market Competition, Credit Availability, and Financial Inclusion 9

2.1.2 The Dominant Position of the Banking Sector in China 12

2.1.3 China's Commercial Banks, Their Efficiency and Performance, and Credit Allocation 13

2.2 Overview of the Shadow Banking Sector 14

2.2.1 Definitions and Size Estimations of Shadow Banking 15

2.2.2 China's Credit Market Architecture and the Position of Lending Marketplaces 17

2.3 The Lending Marketplaces Overview 22

2.3.1 The Definition 22

2.3.2 Platforms and Their Classification 22

2.4 Determinants of Marketplace Loan Outcomes 23

2.4.1 Financial Determinants 24

2.4.2 Demographic Characteristics 25

2.4.2.1 Race *25*

2.4.2.2 Age *26*

2.4.2.3 Gender *26*

2.4.2.4 Regional Information and Social Capital *26*

2.4.3 Other Soft Information 27

2.4.3.1 Friendships *27*

2.4.3.2 Appearances and Videos *27*

2.4.3.3 Narratives *28*

2.4.3.4 General Unverifiable Soft Information *29*

3. Banking Competition and the Use of Shadow Credit from Lending Marketplaces **30**

3.1 Chapter Introduction 30

3.2 Institutional Background 33

3.2.1 China's Banking System 33

3.2.2 China's Marketplace Lending Industry and RRD 34

3.2.3 The Pecking Order of Borrowers in China 36

3.3 Hypotheses Development 36

3.4 Data and Research Design 38

3.4.1 Measuring Banking Market Competition 38

3.4.2 Variables of Interest and Control Variables 44

3.4.3 Summary Statistics 44

3.4.4 Research Design 47

3.5 Empirical Results and Explanations 49
3.5.1 Main Results 49
3.5.2 Heterogeneity Tests 55
3.5.2.1 Heterogeneous Effects from Banks 55
3.5.2.2 Heterogeneous Impacts on Borrowers of Different Ages 56
3.5.2.3 Newcomers or New Personalities? 57
3.5.3 Panel Data Evidence 61
3.6 Robustness Tests 62
3.6.1 Are Large Samples Problematic? 62
3.6.2 Banking Competition or Other Economic Factors? 65
3.6.3 Instrumental Variable Approach 70
3.6.4 Are Branch-based Competition Indices Representative? 73
3.6.5 Are Borrowers on RRD Representative? 76
3.7 Chapter Conclusion and Policy Implications 77
4. Lending Marketplaces and Banks during a Crisis: The Case of COVID-19 79
4.1 Chapter Introduction 79
4.2 Background and Hypotheses Development 82
4.2.1 Lockdown, Nationwide Mobility Restrictions and Recovery from the Pandemic 82
4.2.3 Different Profiles of Borrowers from Banks and Lending Marketplaces 87
4.3 Data and Methodology 87
4.3.1 Data from the Database of NIFA 87
4.3.2 Data from the Commercial Website of lending marketplace RRD 88
4.3.3 Methodology 88
4.3.3.1 Justification of Panel-data Regression Model Settings 88
4.3.3.2 Justification of DID Measurement Model Settings 91
4.4 Measurement Strategies, Measurement Results, and Explanations 94
4.4.1 The Loan Volume 94
4.4.2 The Loan Size 98
4.4.3 The Loan Maturity 102
4.5 Robustness Tests 108
4.5.1 The Robustness Test on the Effectiveness of Time Dummies 108
4.5.2 The Robustness Test on the Pandemic's Indirect Impact on Lending Marketplaces through Banks 109
4.5.3 Why are the Results Insensitive to the Supply Side of Credit? 117
4.6 Chapter Conclusion and Policy Implications 117
5. Do China's Bank Stocks React to their Marketplace Lending Competitors? 119
5.1 Chapter Introduction 119
5.2 Institutional Backgrounds 121
5.2.1 The Underdeveloped Financial Market, Bank Inefficiency, and Credit Misallocation 121
5.2.2 Lending Marketplaces Failures and Volatile Regulation Environment 122
5.3 Research Design and Data Construction 124
5.4 Empirical Results and Explanations 126
5.4.1 Main Results 126

5.4.1.1 Results Based on the Standard Market Model *126*
5.4.1.2 Results Based on the Adjusted Market Model *130*
5.4.1.3 Results Based on the Sample from the Stock Exchange of Hong Kong *133*
5.4.2 Heterogeneity Tests 136
5.4.2.1 Potential Disadvantage I: Fixed-asset-heavy Business Model *136*
5.4.2.2 Potential Disadvantage II: Higher Regulatory Burdens *138*
5.4.2.3 Potential Disadvantage III: Insufficient Applications of FinTechs *140*
5.5 Chapter Conclusion and Policy Implications 144
6. Conclusions and Policy Suggestions 146
7. References 150
Appendix I: Estimates of the Size of China's Shadow Banking Sector 171
Appendix II: The Structures of Web Spiders 173
Appendix III: Chapter 3 — Variable Definitions and Data Sources 176
Appendix IV: Summary Statistics of Chapter 4 179
Appendix V: Chapter 4 — Summary of Variables 182
Appendix VI: Long-term Trends of Funded New Loans from RRD 184
Appendix VII: The Dictionary of FinTech-related Keywords and Other Construction Details. 185

List of Figures

Figure 1: The Volume Trend of Global Shadow Banking 17
Figure 2: The Dynamic Architecture of Formal Banking and Shadow Banking Systems in China 20
Figure 3: Dynamic Banking Competition of Representative Provinces.....42
Figure 4: Daily New Confirmed Cases of China during the First Six Months of 2020 84
Figure 5: Trend of Total Retails of Consumption Goods and Consumption Loans in China's Society85
Figure 6: Intensity of Intra-City Travel 112

List of Tables

Table 1: Geographical Market Share of Commercial Banks 43
Table 2: Summary Statistics 46
Table 3: Main Results 52
Table 4: Heterogeneous Effects from Banks 59
Table 5: Panel Data Evidence 62
Table 6: Bootstrapping 64
Table 7: A DID Identification Strategy 68
Table 8: Instrumental Variable Regressions 72
Table 9: Alternative Measures of Banking Competition 74
Table 10: Results of an Alternative Marketplace 78
Table 11: Impacts of the Pandemic on Funded Marketplace Loan Volume 97
Table 12: Impacts of the Pandemic on Funded Marketplace Loan Sizes – Percentiles and Average 100
Table 13: Impacts of the Pandemic on the Funded Marketplace Loan Maturity – Percentiles and Average 104
Table 14: Impacts of the Pandemic on Funded Marketplace Loan Maturities – Frequencies of k-month Loans 106
Table 15: Robustness Tests on Impacts of the Pandemic on Funded Marketplace Loan Volume 113
Table 16: Robustness Tests on Impacts of the Pandemic on Funded Marketplace Loan Sizes – Percentiles and Average 114
Table 17: Robustness Tests on Impacts of the Pandemic on Funded P2P Loan Maturities – Percentiles and Average 115
Table 18: Robustness Tests on Impacts of the Pandemic on Funded Marketplace Loan Maturities – Frequencies of k-month Loans 116
Table 19: A-share Market Reactions to Adverse Policy Announcements against Lending Marketplaces 128
Table 20: A-share Market Reactions to Adverse Policy Announcements against Lending Marketplaces: Adjusted Market Model 131
Table 21: Hong Kong Market Reactions to Adverse Policy Announcements against Lending Marketplaces 134
Table 22: The Reactions of Banks with Heterogeneous Stickiness to Field Operations 137
Table 23: The Reactions of Banks with Heterogeneous Regulatory Burdens 140
Table 24: The Reactions of Banks with Heterogeneous Applications of FinTechs 143

Abstract

This thesis aims to disentangle the composite interactions between China's commercial banks and lending marketplaces. It also contributes to an understanding of their roles and performances in serving borrowers in the world's largest emerging market.

I first examine whether banking competition affects the creditworthiness of borrowers relying on lending marketplaces. Analysing granular data from two leading online marketplaces, Renrendai (RRD) and Yilongdai (YLD), I find that marketplace borrowers from concentrated banking markets tend to be more creditworthy than those from competitive banking markets. This phenomenon is more pronounced when new banks compete in the banking market, when borrowers are young, or when borrowers are new to the marketplace. Results suggest borrowers may migrate from banks to lending marketplaces when the banking market is concentrated and less inclusive.

I then examine the roles of banks and lending marketplaces in providing credit to individuals and households during the COVID-19 pandemic. Results suggest that lending marketplaces played a role as an alternative to banks in China during this crisis.

Finally, I examine the external wealth effects of the severe interventions of the government against the marketplace lending industry. Using stock data, I find listed banks as traditional credit market incumbents react positively to these exogenous interventions against their competitors. These positive reactions are consistent with the view that the competition from the marketplace lending industry outweighs the synergies that the industry brings. Heterogeneity tests show that banks with more fixed assets proportionally designated to serve personal deposit-and-loan business and banks with higher regulatory costs have greater positive reactions. However, the reactions of bank stocks are insensitive to their applications of financial technologies (FinTechs). These results imply that banks do not face technical

barriers when competing with lending marketplaces. Instead, real disadvantages are likely to be adherence to field operations and regulatory burdens.

1. Overall Introduction

Since the first lending marketplace[1], Zopa, was founded in the United Kingdom in February 2005, a massive amount of literature has emerged discussing various dimensions of this innovative credit intermediary. Its excellent data transparency allows a fundamental understanding of peer-to-peer (P2P) lending relationships, the interactions between creditors (investors) and borrowers, and their behaviours. However, most studies discuss these factors within the marketplace lending industry, yet Zopa's interactions with other credit market incumbents are insufficiently studied. I develop this thesis in the belief that the growth of lending marketplaces is not internally determined. Instead, how lending marketplaces complement the entire credit market and interact with other incumbents may be a key reason for their global prosperity. In this thesis, I treat lending marketplaces as a new type of shadow banking enabled by the internet and FinTechs and contextualise my study in the entire credit market. The thesis contributes to the literature by discussing one of the most important interactions; the nexus between lending marketplaces and commercial banks.[2]

Given their functional similarities and the indispensable role of banks in the global financial system, the nexus between lending marketplaces and banks is well worth exploring. Banks work as credit dealers by purchasing deposits from the public and reselling the credit to borrowers. The profits of their deposit-and-loan business are primarily interest spreads. As primary credit intermediaries, banks play a significant role in most financial systems worldwide. Compared with developed countries, the role of banks is even more essential for developing countries due to the underdevelopment of other financing channels, such as equity and bond markets. Typical lending marketplaces work as credit brokers by organising online platforms for investors and borrowers. Their profits are commission fees. The functional similarities between banks and lending marketplaces raise a series of questions regarding

[1] Lending marketplaces are sometimes referred to as marketplaces or platforms hereafter for brevity.

[2] Unless otherwise specified, the following "banks" refer to "commercial banks".

how they realise long-term coexistence. Specifically, is customer differentiation an essential reason for their long-term coexistence? Is the growth of the lending market due to insufficient financial inclusion in the banking market? Has insufficient local banking competition led to insufficient financial inclusion of local borrowers? And if so, has insufficient local banking competition eventually contributed to the interagency migration of local borrowers and the local popularity of shadow credit from lending marketplaces? Are these two types of credit are substitutes or complements and are their relationship is country-specific? I also answer whether the relative importance of banks and lending markets in providing credit would change in some unique circumstances, such as in a crisis. Finally, I analyse whether lending marketplaces will impact the future of banks and what are the potential disadvantages of banks relative to the lending market.

I use the case of China to develop this thesis. As the biggest emerging economy, its banks dominate the country's financial system. During the study period, the trading volume of China's lending marketplaces also became the world's largest. Moreover, the immature financial system can only provide limited types of credit instruments for private enterprises and customers. Less interference from other credit instruments not of interest means that if a connection between banks and lending marketplaces does exist, it would be most detectable in China. Conclusions derived from the leading development of its lending marketplaces during my study period can also inspire other emerging economies. In the chapter introduction sections, I further explain the reasonability of choosing China in more detail.

Chapter 2 systematically reviews the literature on which this thesis is built. I first describe the international studies on how banking competition affects credit availability and show that the literature is generating mixed evidence. I list studies pointing out the dominance of the banking sector in China and discuss the literature regarding the heterogeneity in efficiency, performance, and tastes for credit allocation by types of its commercial banks. This part of the review reveals that the impact of banking competition is controversial, and most studies

focus on firm borrowers in developed countries. This fact helps me to locate one of the potential research gaps, i.e., how local banking competition affects the financial inclusion of individuals and households[3] in emerging economies. The dominant role of banks in China becomes an essential context of the thesis, especially when banks interact with lending marketplaces. The multidimensional differentiation of banks justifies most of the following tailored heterogeneity tests. I then introduce the counterpart of the banking sector, the shadow banking sector, and describe various definitions and size estimates from researchers. I also summarise the dynamic architecture (Figure 2) of China's formal and shadow banking systems and locate the position of lending marketplaces in the architecture. The architecture reveals the functional similarities of banks and lending marketplaces in channelling credit from initial creditors to ultimate borrowers, a primary reason why they naturally compete. At last, I give the formal definition of lending marketplaces extracted from the literature and summarise their classification. I also summarise the literature discussing the determinants of loan outcomes in lending marketplaces, which guide the details of following model design in this thesis.

Chapter 3 examines how regional banking competition affects the regional popularity of shadow credit from lending marketplaces. I design a novel strategy to examine the impact of banking competition on marginal customers. I jointly analyse data from regional banking markets and lending marketplaces in China and consider the potential interagency migration of these marginal borrowers. To the best of my knowledge, this is the first study to link regional banking competition with the profile of marketplace borrowers. My empirical analysis shows a significant association between regional banking competition and the probability of marketplace borrowers being creditworthy. Marketplace borrowers from more competitive banking markets (i) receive smaller bids from fewer investors, (ii) have lower funding success, (iii) are more likely to be overdue, and (iv) have higher default rates.

[3] I use the terms "individuals and households" and "customers" interchangeably in this thesis.

Heterogeneity tests show the effect is more pronounced when the joint-stock commercial banks (JSCBs) and city commercial banks (CCBs) contribute more competition to the market, the borrowers are young, and the borrowers are new to the marketplace. My explanation for this pattern is that more competition has led to relaxed credit checks by banks. If borrowers in competitive markets still cannot pass the less stringent credit checks and migrate to lending marketplaces, they are typically riskier than those from concentrated banking markets. Marketplace borrowers from concentrated banking markets are, in fact, denied by more stringent standards and would have been financed by the banks if the markets were more competitive. A variety of robustness tests back my explanation.

Chapter 4 focuses on the performances of banks and lending marketplaces during the COVID-19 pandemic. I first develop hypotheses to visualise the impact of the pandemic on China's lending marketplaces. I hypothesise that the pandemic overall decreased loan volumes of pre-existing marketplace borrowers, but the marketplace lending industry also attracted some newcomers from banks, which temporarily shut down their physical branches and thus could not serve some of their customers. I further hypothesise that large-sized loans which originated during the pandemic were mainly contributed by these newcomers from banks. The results of the baseline models support and go beyond my hypotheses. My main results are also found to be robust. Besides my hypotheses, I find that borrowers from banks typically contributed more long-term marketplace loans than pre-existing marketplace borrowers; on the contrary, pre-existing marketplace borrowers tended to borrow more small-sized and more short-term loans than the ex-ante level. The pandemic impacted cities unevenly. Wuhan and surrounding cities in Hubei faced a harder situation than other areas. I also find evidence that impacts on marketplace lending volume may be temporary, but whether impacts on marketplace loan size and loan maturity are also temporary is unclear.

Unlike previous chapters discussing the impact of banks on lending marketplaces, Chapter 5 focuses on a mechanism in the opposite direction. I examine the external wealth effects of

the severe interventions of governments against the marketplace lending industry in China. I make use of the volatile policies against lending marketplaces and test whether listed banks react to these exogenous and intensive interventions on their competitors. This chapter provides evidence regarding the stock market's opinion on whether lending marketplaces significantly affect the future value of banks and whether this effect is positive or negative. I carefully locate events based on the release dates of watershed documents indicating the regulatory volatility and then calculate the cumulative abnormal returns (CARs) of listed financial institutions around the events. When treating nonbank financial institutions as the control group, results strongly indicate that China's listed banks react to the turbulence encountered by their marketplace lending competitors, even though the current aggregated size of these competitors is still small. The empirical results are consistent with the view that competition from FinTech firms outweighs the synergies they bring. I further run heterogeneity tests to analyse how banks with different attributes react differently to these exogenous shocks. Some heterogeneity tests show that differential applications of FinTechs by banks cannot effectively explain their heterogeneous stock reactions, implying that banks do not face technical barriers when competing with lending marketplaces. Instead, I find results suggesting that the potential disadvantages of banks are likely to be adherence to field operations and heavier regulatory burdens. At the end of this chapter, I run an endogeneity test showing that the uninterrupted growth of lending marketplaces before the sanction has not impacted their financial health. The results largely reduce the likelihood that the government cracked down on lending marketplaces due to "bank protectionism" or other implicit guarantees to banks, making these events exogenous to the banking sector. The last chapter concludes the entire thesis and makes comprehensive policy suggestions.

Some limitations exist. The primary limitation is data accessibility. Chapters 3 and 4 investigate the interaction of credit from commercial banks and lending marketplaces from the micro perspective. Most tests are based on loan-level data from lending marketplaces and

macro information from banks. Obtaining loan-level data from banks would be valuable for further research; however, the current study is based on the accessible data obtained to the best of our ability. Future studies can also consider using other models instead of DID-genre models to analyse the panel data. For example, structure breaks are likely to be handled by a vector error correction model (VECM).

2. Literature Review

2.1 Overview of the Banking Sector

I review the global evidence on how local banking market competition affects the financial inclusion of borrowers. Although most studies focus on firm borrowers in the United States and other developed economies, their methodologies and conclusions provide both quantitative and qualitative hints for the development of this thesis. By systematically reviewing the literature, I locate one of the potential research gaps, i.e., how local banking competition affects the financial inclusion of individuals and households in China, the largest emerging economy. This thesis builds on a solid understanding of the banking sector, which dominates the financial system in China. Its pivotal position becomes an important context for developing the entire thesis. This dominant role is essential when banks interact with lending marketplaces. I also summarise studies indicating the differential efficiency, performance, and credit allocation taste among different types of commercial banks, which necessitates tailored heterogeneity tests in the following analysis if applicable.

2.1.1 The Banking Market Competition, Credit Availability, and Financial Inclusion

Mixed evidence is available on how banking market competition influences credit availability. Some studies design models and give explanations from the perspective of information transmission and communication. The model by Petersen and Rajan (1995) illustrates that it is harder for banks in fiercer competition to own informational advantages among competitors and build reciprocal lending relationships with borrowers. They are less likely to internalise the benefits of financing young or distressed firms and consequently cause credit constraints. In line with Petersen and Rajan, Fischer (2000) shows that banks in a concentrated market systematically acquire more information about borrowers before granting credit. This procedure allows banks to provide liquidity without inducing additional information collection costs. He further finds that credit is more available for borrowers in a

concentrated banking market. However, the study of Marquez (2002) focuses on the information dispersion among competing creditors. He finds that competition intensifies the information dispersion among banks. Since every bank becomes only informed about a smaller pool of borrowers, the screening ability of a bank is impaired. Consequently, more risky borrowers can obtain credit. Hauswald and Marquez (2006) further find that as competition increases, banks reduce their investments in acquiring information and become more likely to lend to riskier borrowers.

Unlike theoretical studies focusing on information transfer, more empirical evidence supports that banking competition overall benefits borrowers in various ways. Beck et al. (2004) provide cross-country evidence that higher bank concentration increases obstacles to obtaining credit in countries with economic and institutional underdevelopment. In the United States, new firms in concentrated banking markets face greater difficulty accessing credit than those in competitive banking markets (Cetorelli and Strahan, 2006). Increased banking competition can happen naturally, but can also be caused by external intervention such as deregulation and reforms. Zarutskie (2006) discovers the differential impacts of increased competition on firms of different ages. Following deregulation, newly formed firms are smaller and use substantially less external debt. However, the adverse effect of increased competition is reversed when firms are more established. The studies by Jayaratne and Strahan (1996), and Rice and Strahan (2010) consistently show that banking deregulation in the United States does not benefit small firms by increasing the credit volume. Instead, deregulation improves the quality of bank lending and decreases borrowing costs. Harris et al. (1994) find that banking deregulation in Indonesia improves the volume and quality of channelled credit. Bertrand et al. (2007) show that following the deregulation of the French banking industry in 1985, the market became more inclusive to poorly performing firms.

Empirical evidence from China generally supports the view that banking competition benefits borrowers. More competition encourages banks to lend to small- and medium-sized

enterprises (SMEs) in China (Shen et al., 2009). The competition raised by the entry of foreign banks brings more credit to less opaque firms or non-state-owned firms in China (Lin, 2011). Using a survey on the financial situation of SMEs, Chong et al. (2013) find that lower market concentration alleviates financial constraints faced by SMEs in China. Chemmanur et al. (2020) show that following China's WTO entry and banking industry reforms, banks tend to apply more stringent screening on borrowers and increase their lending quality when facing fiercer competition.

Despite a considerable body of work discussing the impact of banking competition on credit availability for firms, few studies consider how banking competition affects the financial inclusion of individuals and households. Garmaise and Moskowitz (2006) study the side effects of bank mergers, which lead to less market competition. They provide evidence from the United States that neighbourhoods experiencing more bank mergers are subject to higher borrowing costs, subdued local construction and lower real estate prices, an influx of poor households, and a higher crime rate. Sun and Yannelis (2016) find that the increased credit supply following deregulation in the United States raised college enrolment by around 2.6 percentage points. Dick and Lehnert (2010) propose a mechanism by which banking competition improves the financial inclusion of households in the United States. They find that following deregulation, banks are prompted to adopt sophisticated creditworthiness screening technology, allowing for lower loan loss rates, higher lending productivity, and credit extension to previously excluded households. However, they also mention a side effect of deregulation, i.e., it contributes to at least 10% of the rise in personal bankruptcy rates.

As described, extant studies mainly focus on how banking competition affects financial constraints on firms. There are far fewer articles investigating the impact of banks on the financial inclusion of individuals and households, and most of them discuss the situation in the United States. Situations in other major economies, especially large emerging economies like China, have not been adequately studied. To the best of my knowledge, no articles study

the impact of banking competition on customers by jointly considering lending marketplaces as an alternative credit pool and the potential interagency migration of borrowers.

2.1.2 The Dominant Position of the Banking Sector in China

The banking sector plays a pillar role in the financial system of China. Allen et al. (2005) find that the banking system dominates China's financial system. Their calculation shows the ratio of total bank credit to GDP reaches 1.11, even higher than the German-origin countries with a weighted average ratio of 0.99.[4] Unlike the financial system of most developed countries, the size of China's stock market is not comparable to the banking sector in supporting the entire economy. The role of the stock market in allocating resources in the economy is limited and less effective (Allen et al., 2012). A prominent feature of the banking sector in China is the strong presence of state capital in various types of commercial banks, such as state-owned commercial banks (SOCBs), JSCBs, and CCBs. The role of the state-owned capital remains controversial. Allen et al. (2012) find that state-own capital enhanced the ability of banks to maintain relatively healthy functions during the global financial crisis. However, other studies indicate that its strong presence may hinder competition, drag down efficiency, and give rise to credit misallocation, which will be discussed in the next section.

The dominance of banks in China's credit market profoundly influences borrower pecking order. For individual and household borrowers, banks will likely know whether they have borrowed through the shadow banking sector before. Banks in China have multiple channels to know the borrowing history of individuals and households. For example, as regulated by the government, banks are usually third-party fund custodians for shadow banking institutions. Borrowing from the shadow banking sector will signal to banks that customers are short of funds and have high default risks. Rational borrowers are not likely to borrow

[4] According to the descriptions of Allen et al. (2005), all the measures of bank credit to GDP ratios for countries other than China are directly taken from the study of Levine (2002). Levine uses a value-(GDP of each country) weighted approach to calculate these numerical values for countries of each legal origin group. Allen et al. (2005) use the style of Levine to calculate China's bank credit to GDP ratio. The data source is the Almanac of China's Finance and Banking (2000) and China Statistical Yearbook (2000).

from the shadow banking sector if bank credit is available, as the former may affect their obtaining bank credit in the future. Studies often presume that borrowing from banks and shadow banking institutions are not independent decisions of borrowers and that banks are given higher priority in the pecking order of borrowers (e.g., see Butler et al., 2017; Tang, 2019; De Roure et al., 2022; Maskara et al., 2021).

2.1.3 China's Commercial Banks, Their Efficiency and Performance, and Credit Allocation

Studies have shown a prominent type-specific heterogeneity of China's commercial banks in terms of efficiency, performance, and their tastes in credit allocation. The preponderant type is SOCBs, large commercial banks directly controlled by state agencies, including the Ministry of Finance and Central Huijin Company.[5] SOCBs hold the biggest market share in China's banking sector in terms of size and spatial distribution. Using data from 1994 to 2003, Berger et al. (2009) conclude that at least historically, SOCBs were less efficient than foreign banks and other types of banks with minority foreign ownership. García-Herrero et al. (2009) empirically explain the low profitability of China's commercial banks from 1997 to 2004. They find that better capitalisation and less government intervention contribute to better performance, and SOCBs have been the main drag on the sector's profitability. Other studies find SOCBs are more reluctant to finance the private sector; this includes SMEs and consumers (see Allen et al., 2005; Chong et al., 2013; Cong et al., 2019; Ma et al., 2019).

JSCBs are medium-sized commercial banks in China's banking industry. Although government capital maintains its substantial presence in JSCBs, these banks typically have more decentralised ownership (Wang et al., 2018) and are more market-oriented than SOCBs (García-Herrero et al., 2009). JSCBs tend to adopt the organisational structure of modern corporates. Studies show that the overall performance and efficiency of JSCBs are superior to

[5] The six SOCBs in descending order of total assets in 2021 are the Industrial and Commercial Bank of China (ICBC), China Construction Bank (CCB), Agricultural Bank of China (ABC), Bank of China (BOC), Postal Savings Bank of China (PSBC), and Bank of Communications (BOCOM). ICBC, C CB, ABC and BOC are also known as China's "*Big Four*" banks.

SOCBs and CCBs (see Kumbhakar and Wang, 2007; Shih et al., 2007; Fu and Heffernan, 2007). Most CCBs were restructured from urban credit cooperatives (Li et al., 2001; Zhao et al., 2020) and designed to revitalise the local economy by serving the private sector and managing local financial risks (Chen et al., 2021). Compared with SOCBs and JSCBs, CCBs are smaller and typically operate within the provincial-level administrative region (hereafter referred to as *province*) where the bank is headquartered. In addition, CCBs have shown the most significant variance in performance due to a mix of geographical and historical legacies (Shih et al., 2007; Ferri, 2009; Zhao et al., 2020). Unlike SOCBs that have responded more to political pressure to lend, JSCBs and CCBs have been more profit-oriented when allocating their credit (Zhang et al., 2020).

Other minor components in China's banking industry include foreign banks and rural-based banks. Although foreign banks are thought to be more efficient in some dimensions (Berger et al., 2009; Cheng et al., 2015), their influence in China is limited as their branches mainly operate in the most developed cities of China (Luo et al., 2017). Rural-based banks, such as rural commercial banks (RCBs) and rural credit cooperatives (RCCs), are specialised in supporting local agricultural production (Turvey et al., 2014).

2.2 Overview of the Shadow Banking Sector

This section provides macro institutional contexts for studies on lending marketplaces. I describe definitions and estimations of other researchers of the shadow banking sector, a significant counterpart of the banking sector in China. I also summarise the dynamic architecture of China's formal and shadow banking systems, systematically review the shadow banking literature along this architecture, and locate the position of lending marketplaces in the shadow banking sector. Next, I detail the literature on lending marketplaces on which the development of this thesis relies.

A graphical summary of the literature shows lending marketplaces are relatively independent of banks and naturally compete with their deposit-and-loan business.

2.2.1 Definitions and Size Estimations of Shadow Banking

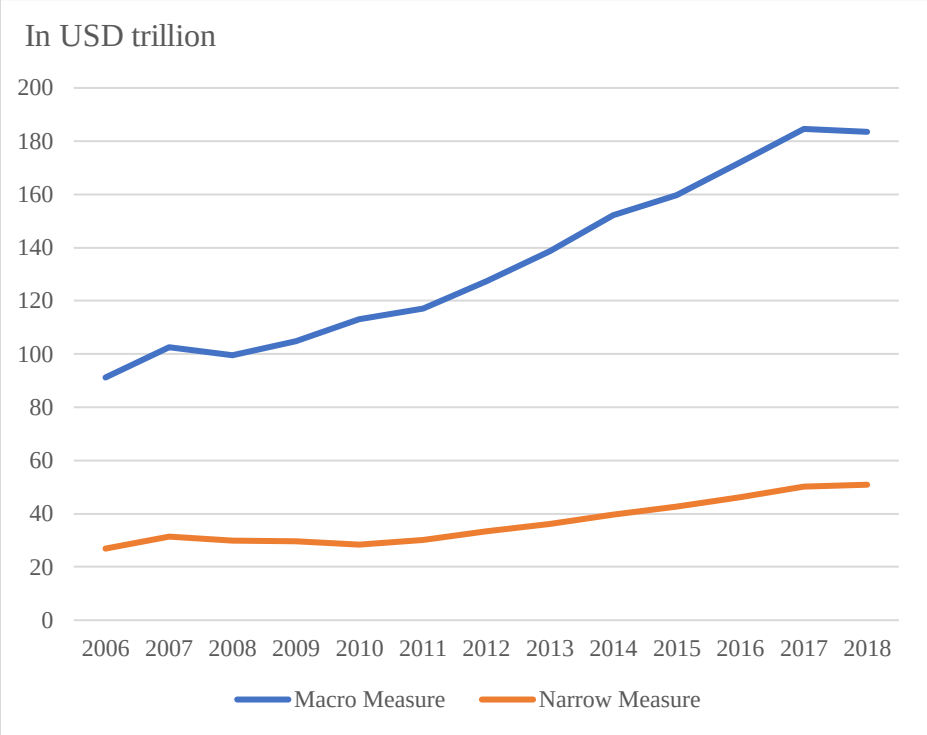
Shadow banking exists both inside and outside the realm of the traditional banking sector. Researchers have different emphases on the exact definition and scope of the shadow banking sector. Pozsar et al. (2010) define shadow banking as financial intermediaries that transfer credit without access to liquidity and other guarantees from central banks and other public formal sectors. Elliott et al. (2015) think shadow banks are financial institutions with similar functions and are subject to similar risks to banks. Other studies apply more general definitions of shadow banking. The Financial Stability Board (FSB) (2011) extends the boundary of shadow banking from institutions to trading activities. The board defines it as entities or transactions outside the traditional banking system that supplies or mediates credit. The International Monetary Fund (IMF) (2014) defines shadow banking as total social financing minus bank loans, equity-like items, and bond issuance, i.e., untraditional and noncore funding. It means some noncore business within banks also belongs to shadow banking. Similarly, Lu et al. (2015) emphasise the substantial volume of off-balance-sheet business within the traditional banking regime. They define shadow banking as an informal market that mediates credit and liquidity, subject to mild regulation and monitoring at most. Detailed definitions by various organisations and researchers are listed in Appendix I.

Despite various definitions and emphases, studies reach a consensus on two perspectives. First, shadow banking outside the formal banking sector means the lack of a strong safety net, few guarantees from central banks, and lighter regulatory burdens. Second, untraditional financial intermediaries, such as microfinance companies and lending marketplaces, belong to the shadow banking sector. In Chapter 4, I discuss the potential disadvantages of banks when competing with lending marketplaces. The higher regulatory costs of banks are probably one of the potential disadvantages.

Global shadow banking has experienced the most rapid growth among financial sectors. Based on the estimates of the FSB (2020), Figure 1 shows its volume has almost doubled in recent years. Researchers have different estimates of the aggregate size of shadow banking in China. There are multiple reasons, such as i) information opacity of China's government agencies and financial institutions; and ii) adoption by researchers of different definitions of shadow banking and estimation methods. I find eight reasonable estimates from the literature, varying from 25 trillion to 72 trillion CNY, or roughly 32% to 79% of the GDPs in corresponding years (see Yi, 2013; Elliott et al., 2015; Sheng et al., 2015; Lu et al., 2015; Ehlers et al., 2018; FSB, 2018; Sun, 2019; FSB, 2020). Shadow banking in China is still smaller than in advanced economies in terms of its share of the national GDP. For example, the FSB (2014) estimates the size of shadow banking in the United States is 120% of its GDP. In its 2019 report, the FSB estimates the narrow (macro) measure of shadow banking reached 77% (278%) of the GDPs of participating jurisdictions in 2018. The shadow banking underdevelopment in China is partially caused by policy uncertainty, which reflects the government's hesitation between its role in boosting the economy (Allen et al., 2005) and its impact on financial system stability (Gruin and Knaack, 2020; He and Li, 2021). A better understanding of how the banking sector interacts with its shadow counterpart is essential for a better solution to this dilemma, justifying the necessity of my research.

Figure 1: The Volume Trend of Global Shadow Banking

The macro measure of shadow banking volume stands for MUNFI (Monitoring Universe of Nonbank Financial Intermediation), a statistical indicator proposed by FSB and used to measure the size of shadow credit. The narrow measure contains a smaller sample of countries where more granular data are available. Volumes are in trillions of US dollars and some exchange rate fluctuation effects have been excluded by using a constant exchange rate from 2018.



2.2.2 China's Credit Market Architecture and the Position of Lending Marketplaces

To better contextualise the marketplace lending industry, I design a graphical summary (Figure 2) of China's formal and shadow banking architecture. Figure 2 shows the credit flows across the formal and shadow banking systems. The details in this figure are based on descriptions from the literature. The figure provides a comprehensive understanding of dynamics and mechanisms and helps organise the shadow banking literature. On the right- (left-) hand side is the summary of initial creditors (ultimate borrowers). In the central (institutions in green boxes) are the primary credit intermediaries. As shown, banks are in the pillar position in both the formal and shadow banking systems. Securities companies, bank wealth management arms, and trust companies are also important players. The literature considers them as the main nonbank financial institutions actively involved in shadow

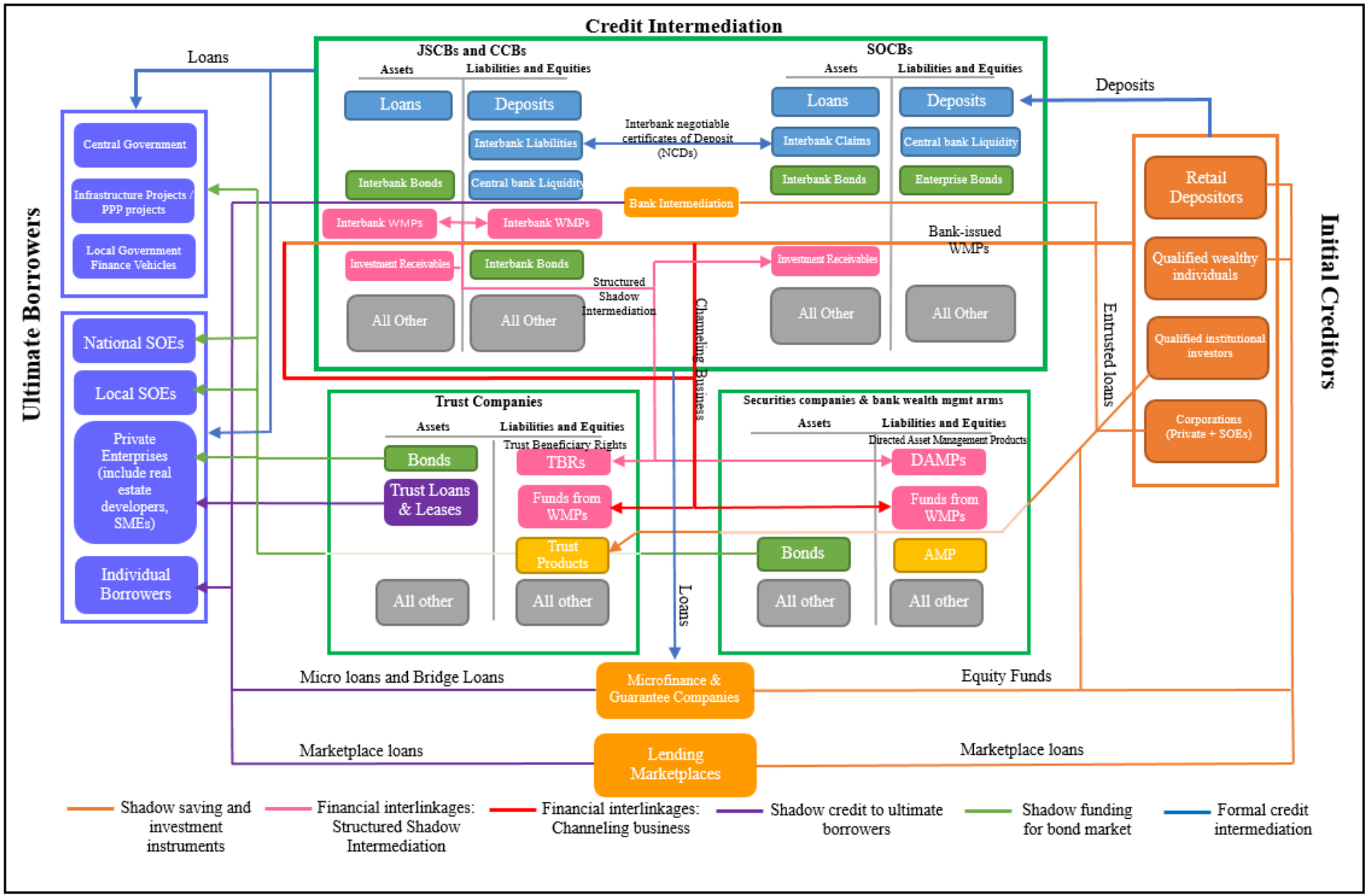
banking (Elliott et al., 2015; Lu et al., 2015; Sun, 2019). The figure also shows that these institutions have substantial connections with banks and largely rely on credit channelled by banks.

By contrast, lending marketplaces, microfinance companies, and guarantee companies in Figure 2 are relatively independent players and primarily rely on credit from initial creditors instead of banks. This independency also means they tend to compete rather than cooperate with banks by serving overlapping or different customers (Rahman and Luo, 2010; Elliott et al., 2015; Liu et al., 2019). As credit intermediation platforms, lending marketplaces share more commonalities with the deposit-and-loan departments of banks than with microfinance and guarantee companies. After the formation of cash pools and security-like products (Zhou et al., 2015; Li et al., 2016; You, 2018; He and Li, X, 2021), the similarity of lending marketplaces to banks increased further.

A prominent feature of Figure 2 is that the players coevolve with laws and regulations. Most shadow banking activities and products do not emerge simultaneously. Instead, new restrictions and prohibitions on some products and activities contribute to the prosperity of others. A major shift most relevant to this thesis is the boom and bust of the wealth management products (WMPs) of banks, which eventually contributed to the growth of lending marketplaces. Studies suggest multiple reasons for the popularity of WMPs (Elliott et al., 2015; Lu et al., 2015; Cai et al., 2019; Walter, 2020; Acharya et al., 2021). First, banks have motivations to do regulatory arbitrage. By selling WMPs, banks wish to circumvent oversight, such as deposit reserve requirements, the loan-to-deposit rate (LDR) cap, and loan quotas for specific industries. Second, banks use WMP vehicles to realise balance-sheet management and window-dressing behaviours. Third, WMPs offer higher rates of return than bank deposits and carry implicit guarantees, while investors constantly seek high-yield alternatives to deposits. By 2017, the size of outstanding WMPs had reached roughly 60% of domestic stock market capitalisation and half of retail savings deposits (Walter, 2020). The

government realised that enormous WMPs were a threat to the stability of the financial system. Along with constructing the macroprudential assessment framework (Klingelhöfer and Sun, 2019), the government ordered banks to sharply decrease their asset pools of WMPs and bring WMPs back on balance sheets. Although shadow credit was considerably squeezed out of the formal banking system, most advantages of WMPs are inherited by marketplace loans.

Figure 2: The Dynamic Architecture of Formal Banking and Shadow Banking Systems in China



(Figure 2 continued)

Blue arrows stand for the intermediation of formal credit. All kinds of initial creditors in China have a tremendous volume of bank deposits, forming the primary pool of credit. Orange arrows represent various shadow instruments of savings and investments. Specifically, bank-related tools are WMPs and entrusted loans. Microfinance and guarantee companies usually package their equities as investment instruments. Lending marketplaces directly link lenders and borrowers and mediate credit in the form of marketplace loans. Purple arrows are shadow credit flows from intermediaries to ultimate borrowers. Red and pink arrows are the financial interlinkages between banks and other institutions. They represent the industrial cooperation and accounting practice to transfer shadow credit across institutions. Specifically, red arrows stand for the ordinary channelling business, where WMPs from banks are directly recorded as liabilities in the balance sheets of trust companies, securities companies and wealth management arms. Pink arrows stand for the structured channelling business, where WMPs from banks are repackaged as TBRs (Trust Beneficiary Rights) or DAMPs (Directed Asset Management Plans) in the balance sheets of these institutions. Green arrows are credit flows through main financial institutions holding bonds issued by governments and firms. It is also worth noting that the bond market is one of the major destinations for WMPs channelling.

2.3 The Lending Marketplaces Overview

2.3.1 The Definition

Typical marketplace lending describes an internet-based procedure of loan intermediation between individual lenders and individual borrowers where online platforms only provide intermediary services while other traditional financial institutions are not directly involved (Bachmann et al., 2011; Herzenstein et al., 2011; Lu et al., 2015; Ehlers et al., 2018). However, increased competition among marketplaces leads to the emergence of variant platforms. These variants are no longer limited to pure intermediary services but start to issue security-like products and pool invested money (Zhou et al., 2015; Li et al., 2016; You, 2018; He and Li, X, 2021).

2.3.2 Platforms and Their Classification

The first online lending marketplace, Zopa, was founded in the United Kingdom in 2005. In 2007, one of the largest marketplaces in the United States, Prosper, opened its database, followed by many other platforms. Data openness significantly facilitated the related research on economics, finance, information technology, and other social science fields (Bachmann et al., 2011). Since then, the marketplace lending industry has experienced great development in terms of volume and forms. Most platforms choose to operate within the country where they were established due to various regulatory frameworks across countries (Berger and Gleisner, 2009).

Lending marketplaces can be classified from various perspectives. For example, based on operational purposes, they can be classified as commercial or non-profit platforms (Ashta and Assadi, 2009). While most commercial platforms run within national markets, non-profit platforms usually operate globally and aim to help people in developing countries out of poverty. Their global operation is enabled by their skills in cooperating with local microfinance institutions worldwide (Xu et al., 2010). Commercial lenders usually require reasonable returns for bearing risk, whereas non-profit lenders wish no or little compensation for the risk they voluntarily take (Bachmann et al., 2011). Commercial platforms have the lion's share in this industry and can be further classified based on their specialised fields. For example, representative platforms focusing on consumer loans are Lending Club (the United States), Prosper (the United States), and Zopa (the United Kingdom). Famous platforms focusing on business loans include Funding Circle and Assetz Capital (the United

Kingdom). There are also many platforms specialising in other fields. Another classification standard is based on pricing strategies. Some platforms adopt an auction-based process to determine loan rates, whereas others set loan rates for investors based on the characteristics of the borrowers. China's commercial lending marketplaces specialise in initiating consumer loans and small business loans. They typically choose to set reasonable loan rates for potential lenders

2.4 Determinants of Marketplace Loan Outcomes

Lending marketplaces allow researchers to examine in detail how lending outcomes are determined. Lending marketplaces are typically subject to different regulations from commercial banks. Their intermediary role means: i) they generally do not have the same deposit reserves as banks; ii) they are not backed by safety nets and usually do not receive implicit government guarantees. Compared with bank depositors, marketplace lenders are directly exposed to more risks from borrowers. Therefore, lending marketplaces are motivated to disclose more details about borrowers and their applications to the public during their early development. Vallee and Zeng (2019) find that sophisticated investors use public information more thoroughly and systematically outperform other investors. Although the participation of sophisticated investors improves screening, it also creates adverse selections among investors. In maximizing the transaction volume, platforms increase pre-screening intensity and decrease information provision to the public after their early development. Their sophisticated outperformance of investors shrinks due to this transition. Vallee and Zeng (2019) show the essentiality of borrower information in predicting loan outcomes. In this section, I systematically review the literature extracting loan outcome determinates from the disclosed information.

Researchers are curious about the factors determining the application outcomes, the interest rates charged, and the loan performance, and extensive related literature emerges. Extant literature discusses possible determinants from three perspectives, i.e., financial determinants, demographic characteristics, and social capital and soft information. Studies discussing such determinants are one of the most prosperous strands of marketplace-lending-related literature. Various analytical techniques are adopted. Researchers use text mining techniques to process soft information. They use logistic regressions and instance-based methods to test the

explaining power of potential determinants (e.g., see Serrano-Cinca et al., 2015; Guo et al., 2016; Lin et al., 2017; Polena and Regner, 2018). This strand of literature provides a fundamental understanding of borrower risk and creditworthiness, providing guides and techniques for my following model designs.

2.4.1 Financial Determinants

Financial determinants, also known as standard information or hard information, are the financial characteristics of borrowers typically considered by banks and other financial institutions as major indicators of their creditworthiness. Typical financial characteristics include a borrower's credit rating, monthly income, monthly expenditure, real estate ownership and mortgages, and debt-to-income ratio (Bachmann et al., 2011).

Ravina (2019) comprehensively studies the influence of beauty and personal characteristics in lending marketplaces by using the data from Prosper. Although she has focused on the demographic attributes of borrowers and soft information, her research still reveals how standard information matters in this market. In short, investors on Prosper react to hard information in the same way as financial institutions. They prefer borrowers with higher credit scores, higher incomes, better employment records, and better credit histories. Higher credit levels and higher incomes lower the interest rates charged, whereas delinquencies, public records, and bigger loan requests increase them. Credit scores, incomes, employment status and homeownership affect delinquency rates just as traditional theory expects.

Iyer et al. (2016) take advantage of their privileged access to borrower credit information, which is unavailable for both marketplace lenders and borrowers, to investigate the inference performance of these lenders. They find that investors infer creditworthiness mainly according to standard information such as a borrower's debt-to-income ratio, delinquency frequency, and credit inquiry records. In contrast, non-standard or soft information only has little explanatory power for the interest rate variation. However, their results also show that the importance of non-standard information is more significant when judging low-end borrowers. Herzenstein et al. (2008) draw similar conclusions. By studying a dataset of 5,370 completed marketplace loan transactions, they find that although demographic attributes do affect the chance of funding success, their effects are minor compared with the effects of the financial information of borrowers.

However, the conclusions of Herzenstein et al. (2008) and Iyer et al. (2016) may be inapplicable in emerging economies where financial disclosure is traditionally insufficient. Tao et al. (2017) analyse a large sample of loan applications in China and find borrowers who earn higher incomes or own cars are more likely to get loans, pay lower interest rates, and less likely to default. However, their credit grades are not an effective indicator of loan performance. A reason is that the credit rating system is developed by a platform, whereas the more accurate credit ratings measured by official credit bureaus are inaccessible to the public.

2.4.2 Demographic Characteristics

The prosperous marketplace lending industry has contributed to increased transparency of information disclosure, allowing researchers to conduct detailed studies on how demographic characteristics impact the application outcome and loan performance. Such demographic characteristics include gender, race, age, and region. Researchers are interested in developing more accurate models for predicting defaults, understanding the behaviour and psychology of lenders and borrowers, or investigating whether discrimination exists.

2.4.2.1 Race

Pope and Sydnor (2011) find evidence of significant racial disparities based on a sample of Prosper applications from June 2006 to May 2007. Loan listings from black borrowers are 25 to 35 per cent less likely to receive funding than those of white borrowers with similar credit profiles. Nevertheless, investors lending to black borrowers earn lower net returns. They manage to understand this phenomenon based on two kinds of discrimination – taste-based and statistical discrimination. However, they admit that any kind of discrimination cannot solely explain these results. If the taste-based discrimination is true, higher net returns for investing in loans to blacks should be observed; if the statistical discrimination is true, no differences in net returns should be observed, as higher interest rates should correctly compensate for the higher default rates. Ravina (2019) contradicts these findings by arguing that black borrowers are not discriminated against in terms of the chance of getting loans. She claims that racial discrimination is subtly reflected in the interest rates black borrowers must pay to get loans. According to her calculation, successful black borrowers need to pay interest rates on average 1.4 percentage points higher.

2.4.2.2 Age

Although no literature is dedicated to explaining how a borrower's age matters, many studies mention the explanatory power of age. For example, Pope and Sydnor (2011) find that borrowers younger than 35 have a 0.4 to 0.9 percentage points higher chance of being funded than the base group (35 to 60 years old), while borrowers older than 60 are 1.1 to 2.3 percentage points less likely to acquire a loan than the base group. Lin et al. (2017) find that in China's marketplace lending industry, each additional year of age increases a borrower's default risk by 1.2% on average, ceteris paribus.

2.4.2.3 Gender

Empirical research by Pope and Sydnor (2011) shows that among successful borrowers, single females can get a 0.4 percentage points discount in interest rates on average, though the estimated return of loans to females is about two percentage points lower than loans to males, if all else is equal. Chen et al. (2017) investigate gender discrimination in China's lending marketplaces and find that female borrowers are more likely to be funded at the cost of higher borrowing interest rates. However, default rates for female borrowers are significantly lower than those for male borrowers. These facts are consistent with the hypothesis that China's case is a mixture of statistical and taste-based discrimination. Barasinska and Schäfer (2014) study the condition in Germany and claim that gender is not contributing to German borrowers' chance of receiving funds from platform investors.

2.4.2.4 Regional Information and Social Capital

The regional information of borrowers is highly informative, as investors can further infer risk through various dimensions of information attached to this variable. Studies show that the home bias of platform investors and other forms of regional discrimination mix rationality and irrationality. In both cases, regional information can affect funding success (Lin and Viswanathan, 2016; Wang, T. et al., 2021). The rational inference of investors implies that regional information can potentially reflect borrower risks. Other studies examine potentially explanatory dimensions behind regional information. For example, Hasan et al. (2022) find that borrowers from regions with higher social capital are associated with better funding outcomes and lower default rates.

2.4.3 Other Soft Information

Besides demographic factors, other soft factors are less measurable yet still influential. These soft factors include social networks, visual impressions of borrowers, and narratives. Researchers are interested in this field and present some interesting findings.

2.4.3.1 Friendships

Friendships here mean social networks within a lending marketplace. This relationship is usually based on kinship, real-world friendships, or transaction histories. Platform investors use a borrower's social networks to infer creditworthiness, especially when standard financial information cannot provide further distinctiveness (Herrero-Lopez, 2009). Freedman and Jin (2008) find that loans with endorsements and bids from friends tend to have repayments on schedule and significantly higher rates of returns. They conclude that a borrower's friends may have information unavailable to other lenders to identify their default risks. Peer monitoring within social networks may also motivate borrowers to perform well. Lin, Prabhala, and Viswanathan (2013) treat friendships as signals of high credit quality in lending marketplaces where severe information asymmetry and adverse selection exist. They find that borrowers on Prosper with credible friends are more likely to get loans ex ante and less likely to default ex post. Freedman and Jin (2017) do similar research on the online social networks of borrowers. They agree that borrowers with social ties in Prosper are more likely to have loans funded and receive lower interest rates. However, they also find that the repayment performance of these borrowers is worse, necessitating a further distinction of various social ties. They further claim that lenders react differently to social ties, and friend endorsement is the most positive social tie in a lender's view, suggesting that social networks with some financial stake are more valued. It is worth noting that they partially overturn their 2008 conclusions.

2.4.3.2 Appearances and Videos

Duarte et al. (2012) focus on how the appearances of platform borrowers affect their borrowing outcomes. They found that visual impressions of trustworthiness help borrowers on Prosper get loans more easily, and it is also a predictor of transaction outcomes. Jin et al. (2019) implement neuroscience techniques to study how lenders react differently to visually attractive and unattractive borrowers. Their research shows that, at the

behavioural level, lenders need less reaction time when deciding to fund attractive borrowers than unattractive borrowers. At the brain level, larger loan requests trigger larger error-related negative amplitudes (ERN) than smaller loan requests for unattractive borrowers. However, it is not the case for attractive borrowers. They argue that the attractive appearances of borrowers may modulate the risk perceptions of lenders, and thus lenders may become more tolerant of possible defaults. This phenomenon is more significant for attractive female borrowers who convey more trustworthy impressions. Wang et al. (2019) study the role of video information using a sample from a lending marketplace in China and suggest that: i) riskier borrowers are more likely to provide video information; ii) these borrowers can get more credit and pay lower interest rates by uploading their video information.

2.4.3.3 Narratives

Pera et al. (2016) explain the general meaning of self-storytelling in a collaborative community of sharing economies. They find that powerful self-storytelling allows an attractive positioning and helps build reputations among related others. Herzenstein, Sonenshein, and Dholakia (2011) study how borrower narratives influence the potential lender decisions using data from Prosper. They find that the unverifiable qualitative information from these narratives has spillover effects on the lending decisions of investors. Verbal descriptions conveying reliability and trustworthiness are associated with more loan funding yet more future performance uncertainty. Dorfleitner et al. (2016) study two leading European platforms and conclude that spelling errors, text lengths, and positive emotion-evoking keywords may predict the funding probability of marketplace loans, but the predictive power depends on the platform design and the requirement of credit scores. They also find that conditional on being funded, text-related information is basically irrelevant to the default rates. Chen et al. (2018) conduct another interesting study. They investigate how the amount of punctuation used in loan descriptions influences the lending outcome and find that excessive usage of punctuations worsens the lending outcome in terms of funding possibility and borrowing costs. They give possible explanations for this phenomenon: first, the overuse of punctuation affects the readability of a loan description; second, it may leave potential lenders with an impression of a borrower's low self-control, poor cognitive ability, and overconfidence in their repayment ability.

2.4.3.4 General Unverifiable Soft Information

Literature also discusses the aggregate influence of general unverifiable soft information. Michels (2012) gives a quantitative measure of this aggregate influence. He points out that such unverifiable disclosure on Prosper contributes to a 1.27 per cent reduction of borrowing costs and an 8 per cent increase in bidding activities. Iyer et al. (2015) highlight the importance of peer views and screening in enhancing lending efficiency. They find that peer lenders predict marketplace loan defaults with 45% greater accuracy than a borrower's exact credit score. Moreover, peer lenders get 87% of the predictive power of an econometrician who observes all standard financial information about borrowers.

3. Banking Competition and the Use of Shadow Credit from Lending Marketplaces

3.1 Chapter Introduction

There is growing recognition of banking competition as an antecedent of financial inclusion. A considerable body of work discusses how banking competition affects the financial inclusion of firms. However, few studies consider how banking competition affects the financial inclusion of individuals and households. Especially, the channels through which banking competition affects marginal customers are unclear. I fill this gap by examining one of the possible channels, i.e., whether banking competition influences screening standards of creditworthiness by banks.

I design a novel strategy to examine the impact of banking competition on marginal customers. I jointly analyse data from regional banking markets and lending marketplaces in China and consider the potential interagency migration of these marginal borrowers. To the best of my knowledge, this is the first study to link regional banking competition with the profile of marketplace borrowers. I use data from China, an emerging market where such migration is most detectable. China has the most bank-dominated financial market globally and boasts the largest marketplace lending market during the study period. Further, formal alternatives to bank credit in China are underdeveloped (Allen et al., 2005), so the migration of borrowers from banks to lending marketplaces, if it exists, would be most practical and readily observable.

I am inspired by the extant shadow-banking literature, which recognises the role of shadow-banking intermediaries, such as lending marketplaces and other FinTech companies, in providing credit to underbanked populations (Elliott et al., 2015; Lu et al., 2015; Butler et al., 2017; Tang, 2019; Bao and Huang, 2021). The role of lending marketplaces as a resort for underbanked customers allows me to observe the competition-sensitive strategies of banks for screening their borrowers. To capture the influence of regional banking markets, I manually merge the branch information of commercial banks and construct multiple provincial indices of competition. I also design five indicators to measure the ex-ante and ex-post creditworthiness of marketplace borrowers. Drawing from a sample of 608,407 loan applications on RRD, a leading lending marketplace in China, over the 2011 to 2015 period, I present my findings.

My empirical analysis shows there is a significant association between regional banking competition and the probability of marketplace borrowers being creditworthy. Specifically, I find that, all else being equal, marketplace borrowers from more competitive banking markets (i) receive smaller bids from fewer investors, (ii) have lower funding success, (iii) are more likely to be overdue, and (iv) have higher default rates. Heterogeneity tests show the effect is more pronounced when the joint-stock commercial banks (JSCBs) and city commercial banks (CCBs) contribute more competition to the market, the borrowers are young, and the borrowers are new to the marketplace.

My explanation for this pattern is that more competition has led to relaxed credit checks by banks. If borrowers in competitive markets still cannot pass the less stringent credit checks and migrate to lending marketplaces, they are typically riskier than those from concentrated banking markets. Marketplace borrowers from concentrated banking markets are, in fact, denied by more stringent standards and would have been financed by the banks if the banking markets were more competitive. A variety of tests confirm the robustness of my empirical results, including accounting for potential endogeneity. The tests show I largely avoid the omitted variable bias, i.e., the association between banking competition and the creditworthiness of marketplace borrowers is due to some unobservable confounders. My results imply that banks in competitive markets tend to expand credit to marginal individuals and households rather than squeeze them out. They also suggest that a less competitive banking market may encourage the use of shadow credit and interagency migration of borrowers occurs when banking market concentration is high. Banking competition overall increases the financial inclusion of households and individuals.

My study contributes to the strand of literature that studies how banking competition influences the level of financial inclusion. The role of bank market power remains controversial. On the one hand, market power may motivate banks to fund young or distressed firms and promote financial inclusion by favouring the formation of reciprocal lending relationships (Petersen and Rajan, 1995). On the other hand, it is argued that, in overall terms, the increase in competition contributes to a more inclusive credit market (e.g., see Beck et al., 2004; Cetorelli and Strahan, 2006; Rice and Strahan, 2010; Chong et al., 2013; Leon, 2015; Love and Martínez Pería, 2015). Moreover, lending relationships are also compatible with greater banking competition (see Boot and Thakor,

2000; Degryse and Ongena, 2007). Although most pre-existing studies focus on how competition impacts the financial inclusion of firms, my study shows that individuals and households can benefit from enhanced banking competition. I doubt that, unlike firms, it may be significantly more difficult for banks to build reciprocal relationships with individuals and households in the consumer credit market, so customers hardly benefit from higher concentration. Further, I suggest customers benefit from more banking competition through relaxed credit checks, enriching the literature about the relationship between creditor competition and customer wellbeing (see Garmaise and Moskowitz, 2006; Dick and Lehnert, 2010; Sun and Yannelis, 2016; Butler et al., 2017; Gissler et al., 2020).

Results of heterogeneity tests in this chapter are some necessary conditions of information asymmetry and adverse selection. Broecker (1990) predicts that due to adverse selection, the proportion of applicants who pass the credit checks of at least one bank increases, so the average creditworthiness decreases. The model developed by Sharpe (1990) suggests that competition shifts the credit allocation toward lower-quality borrowers because of information asymmetry and adverse selection faced by "outside" banks. Marquez (2002) uses a model where, instead of being *less willing* to screen out low-quality borrowers, banks in a competitive market are *less capable* of screening out low-quality borrowers due to information dispersion and increased information asymmetry among creditors. Unlike their theories focusing on firm financing, my results suggest that information asymmetry and adverse selection also explain less stringent credit checks by banks on individuals and households when facing greater competition.

Finally, my work adds to the fast-growing literature on the nexus between bank credit and shadow credit. There is mixed evidence of whether these two types of credit are substitutes or complements. Using data from the United States, Tang (2019) finds that marketplace loans substitute rather than complement bank loans as banks and lending marketplaces serve the same clientele in terms of borrower quality. However, using data from Germany, De Roure et al. (2022) find that marketplace loans are riskier than bank loans, indicating that these two types of credit are not perfect substitutes. My work provides new perspectives. First, the literature implies that borrowing from banks and marketplaces is not based on independent decisions of borrowers, and that banks are preferred by borrowers. If borrowers prefer and compete for bank credit, theoretically, a complete

overlap of bank customers and marketplace customers is not likely to occur. Second, a borrower's preference for bank credit may depend on whether the financial market is bank-dominated. In countries where formal and informal alternatives to bank credit are readily available, such as in the United States, borrower preference for bank loans may not be significant. By contrast, in economies where the financial market is much more bank-dominated, such as in Germany and China, borrower preference for bank loans may be stronger, which explains why bank credit and marketplace credit in these countries cannot be treated completely as substitutes.

The remainder of this chapter is organised as follows. Section 3.2 introduces the institutional background of China's banking system, the operational mechanism of online marketplace lending, and the borrowing preference of China's borrowers. Section 3.3 reviews the literature on banking competition and credit reallocation and develops testable hypotheses. Section 3.4 explains the approach of variable construction, the data, and the methodology used. Empirical results are presented and discussed in Section 3.5. Section 3.5 also deals with heterogeneity testing and provides panel data evidence. The results of robustness tests are presented in Section 3.6 and Section 3.7 concludes the chapter.

3.2 Institutional Background

3.2.1 China's Banking System

China's banking industry is dominated by SOCBs in terms of size and distribution. In 2011, SOCBs owned more than 50 per cent of total banking assets of the entire country.[6] Although their market share in terms of the total assets dropped below half in 2015, they remain the pillar of China's banking sector. Empirical studies show that, at least historically, SOCBs are less efficient (Berger et al., 2009) and more reluctant to finance the private sector; this includes SMEs and consumers (see Allen et al., 2005; Chong et al., 2013; Cong et al., 2019; Ma et al., 2019).

JSCBs are medium-sized commercial banks in China's banking industry. Although government capital maintains its strong presence in JSCBs, these banks typically have more decentralised ownership than SOCBs. JSCBs tend to adopt the organisational structure of modern corporates. Studies show that the overall

[6] Data source: China Banking Regulatory Commission. (2016). *China Banking Regulatory Commission 2015 annual report.* Beijing: China Finance Press.

performance and efficiency of JSCBs are superior to SOCBs and CCBs (see Kumbhakar and Wang, 2007; Shih et al., 2007; Fu and Heffernan, 2007).

Most CCBs were restructured from urban credit cooperatives and designed to revitalise the local economy by serving the private sector and managing local financial risks. Compared with SOCBs and JSCBs, CCBs are smaller and typically operate within the province where the bank is headquartered. In addition, CCBs have shown the greatest variance in performance due to a mix of geographical and historical legacies (Shih et al., 2007).

Other minor components in China's banking industry include foreign banks and rural-based banks. Although foreign banks are thought to be more efficient in some dimensions (Berger et al., 2009; Cheng et al., 2015), their influence in China is limited as they only operate in the most developed cities of China. Rural-based banks, such as rural credit cooperatives, are specialised in supporting local agricultural production.

3.2.2 China's Marketplace Lending Industry and RRD

Marketplace lending, also commonly referred to as P2P lending, describes an internet-based procedure of credit intermediation between individuals where marketplaces only provide intermediary services. Other traditional financial institutions are not directly involved in this procedure. China's marketplace lending industry started in 2007. Like other FinTech institutions which channel shadow credit, its emergence and prosperity are due to the significant barriers many low-income households face when accessing the formal banking sector (Butler et al., 2017; Tang, 2019; Bao and Huang, 2021).

My proprietary data are collected from RRD, one of the largest lending marketplaces in China. Since its official launch in September 2010, RRD has attracted over 2.5 million members and as of December 2015 has successfully facilitated 13.1 billion RMB in loans. Like most relevant studies (Hasan et al., 2022; Liao et al., 2021), I do not include data on the latest years for two reasons: (i) after 2015, the Chinese government's attitude towards the marketplace lending industry changed from supporting its free development to being vigilant against the systemic risks it may cause and restricting its development. I exclude data after 2015 to avoid the

unmeasurable confounding impact of the government's inconsistent policies; (ii) I cannot get the repayment outcomes of some loans after 2015.

Before listing loan applications on RRD, borrowers are required to first register on the website and upload necessary information, including the scanned ID card (both sides), cell phone number, and their bank account to receive the borrowed money. To verify ID authenticity, RRD requires borrowers to upload a photo of themselves holding their ID cards (the side showing the ID number). To verify information authenticity, RRD requires borrowers to provide additional evidence of their residence address, employment, income, education, marital status, real estate ownership, and mortgage status. The most important information, the residential address, is stringently checked by RRD to enable the contingent field investigation and, in the worst scenario, on-site collections in the future. Specifically, RRD requires proof of the address such as bank statements and phone, water, or electricity bills. I identify a borrower's home province based on the residential address. To apply for loans, borrowers need to summarise the purpose of the loan and write a detailed description. They also need to specify the desired loan amount and maturity. A noticeable feature of RRD is that loan rates are not negotiated by borrowers and lenders. Instead, loan rates are assigned by the platform. All personal information, except scanned ID and photographs, are disclosed along with the application form on the platform.[7]

Most loan applications receive bids from multiple investors during the listing period (several days). According to the policy of RRD, a successful application cannot be partially funded. Therefore, any applications that do not reach full subscription from investors will be failed and withdrawn. Once a successful loan application is confirmed by RRD, funds will be transferred from the lender(s) to the bank account designated by the borrower. RRD will charge a brokerage fee to the borrower and an interest spread to the lender(s) for facilitating the loan.

Next, borrowers are obligated to repay principal and interest on a monthly and equal basis. Repayments are proportionally distributed to the lenders after RRD extracts the brokerage fee and the interest spread. If a repayment is overdue, which means a certain round of principal and interest were not repaid by the scheduled

[7] Duarte et al. (2012) show that on Prosper, a famous US-based lending marketplace, trustworthy appearance relates to better funding outcomes and actual creditworthiness of borrowers. The policy of RRD in not disclosing borrowers' photographs simplifies the analysis in this chapter.

time, RRD makes several attempts to collect the repayment; this includes texting and phoning the borrower, contacting the borrower's employer, and conducting on-site collections. RRD also records the overdue times of borrowers before they repay all the principal and interest. If the borrower eventually defaults, RRD will be responsible for repaying the principal and interest to the lenders and marks the loan outcome as default. All loans are unsecured loans, and their maturity ranges from 1 month to 48 months.

3.2.3 The Pecking Order of Borrowers in China

Borrowers can choose between borrowing from banks or marketplaces. Studies often presume that borrowing from banks or marketplaces are not independent decisions of borrowers, and that banks are given higher priority in the borrower pecking order (e.g., see Butler et al., 2017; Tang, 2019; De Roure et al., 2022; Maskara et al., 2021). Most marketplace borrowers can be treated as customers who are at least underserved by banks. A downward migration of marginal borrowers to marketplaces possibly explains the growth of the marketplace lending industry (Claessens et al., 2018).

Compared with borrowers in developed countries, borrowers in China have a greater tendency to borrow from banks rather than marketplaces due to the pillar role of the banking sector. Further, banks in China are likely to know whether an individual has borrowed through a marketplace before, given that banks are third-party fund custodians for platforms and credit receivers for marketplace borrowers. Borrowing from marketplaces will signal to banks that customers are short of funds and have high default risk. Rational borrowers are not likely to borrow from marketplaces if bank credit is available, as the former may affect their obtaining bank credit in the future.

3.3 Hypotheses Development

My study is motivated by a desire to understand the role of greater banking competition on credit reallocation. Competing models and empirical studies suggest that both stronger market power and stronger competition are likely to reallocate credit to marginal borrowers.

According to the model of Petersen and Rajan (1995), stronger market power increases financial inclusion because it facilitates the formation of reciprocal lending relationships. Banks in such relationships are more

likely to finance less creditworthy borrowers because they can extract future rents from these borrowers. Competition deteriorates financial inclusion, as it discourages the formation of reciprocal lending relationships. It is harder for banks in greater competition to share future "surplus" with borrowers, as rents from those with better performance can be easily competed away by other banks. Moreover, banks facing greater competition may become more cautious in screening poorly-performing and less creditworthy borrowers (Bertrand et al., 2007; Chemmanur et al., 2020). If this hypothesis is true, when banking competition increases, borrowers are more likely to fail the credit checks, and at least some of them will migrate to marketplaces according to their pecking order.

However, more competition may also contribute to credit reallocation to less creditworthy borrowers at the extensive margin and thus increase financial inclusion. Studies supporting this view focus on the information asymmetry among creditors. The model developed by Sharpe (1990) suggests that competition shifts the credit allocation toward lower-quality borrowers because of information asymmetry and adverse selection faced by "outside" banks. When an "outside" bank competes for incumbent bank customers via lower interest rates, the adverse selection makes it difficult for the entrant to draw good customers without attracting riskier ones as well. In the model of Marquez (2002), with more competing banks, the proprietary information of borrowers becomes more dispersed. As each bank is only informed about a smaller pool of borrowers, a bank is less capable of screening out low-quality borrowers. Overall, increased financial inclusion resulting from more competition is not regarded as an outcome voluntarily pursued by banks, but it does increase the welfare of customers. Similarly, if this hypothesis is true, when banking competition decreases, borrowers are more likely to fail the credit checks of banks, and at least some of them will migrate to lending marketplaces according to their pecking order.

No matter which hypothesis is true, regional banking competition is likely to significantly influence the migration of borrowers from banks to lending marketplaces and change a marketplace borrower's chance of being creditworthy. I will test the role of banking competition against that of bank market power in reallocating credit to marginal borrowers by observing borrowers who migrate to lending marketplaces. My first hypothesis can be stated as follows:

Hypothesis 1: All else being equal, marketplace borrowers from concentrated banking markets are more likely to be creditworthy than marketplace borrowers from competitive banking markets.

Beyond an association relationship described in *Hypothesis 1*, I further propose that this association relationship reflects the positive impact of banking competition on financial inclusion, which is consistent with a causal interpretation. Marketplace borrowers from concentrated banking markets are, on average, more creditworthy because the screening standards of banks in a concentrated market are more stringent than those of banks in a competitive market. Borrowers from concentrated banking markets are, in fact, denied by more stringent standards and would have been financed by the banks if the banking markets were more competitive. Marketplace borrowers from competitive banking markets are on average less creditworthy as, due to greater information asymmetry and adverse selection, banks in competitive markets are less capable of screening out risky borrowers, and the banking markets become more inclusive than before. If borrowers in such competitive and inclusive banking markets still have to rely on marketplaces, they are likely to be even less creditworthy than borrowers at the extensive margin. My second hypothesis can be stated as follows:

Hypothesis 2: Banking competition improves the financial inclusion of individuals and households through relaxed credit checks. Consequently, underbanked borrowers from competitive banking markets become less creditworthy.

3.4 Data and Research Design

3.4.1 Measuring Banking Market Competition

I collect the detailed information of bank branches by merging datasets from the websites of commercial banks, the financial license database of China Banking and Insurance Regulatory Commission (CBIRC), and data from Tianyancha – a commercial database specializing in business registry information. I further calculate the dynamic competition indices of every province based on the opening (closing) date of all (some) branches.

Table 1 reports the geographical market share (in terms of bank branches) of different banks across provinces in four economic zones.[8] There are six national SOCBs in China.[9] My data shows that in 2015 the six SOCBs owned 124,923 branches across the country. Their branches are widely distributed and dominate the banking market in every province. Three panels of Table 1 show a nationwide decrease in their market share during the study period. These panels also show an increasing trend in their market share from the east (economically developed) to the west (economically underdeveloped).

There are 12 JSCBs in China that are allowed to open branches freely across the country like SOCBs. Table 1 shows that their market share increases in most areas of China during the study period. In 2015, the JSCBs owned 16,402 branches in total. However, in overall terms, JSCBs develop into regional inter-provincial banks as they are more profit-driven than SOCBs and the profit margin for opening branches in economically underdeveloped provinces is low. JSCBs generally prefer to set up branches in the eastern coastal areas, showing a decreasing presence from the east to the west. Moreover, JSCBs exhibit heterogeneous expansion strategies. JSCBs established earlier have wider market penetration and greater market power in most developed eastern provinces; in contrast, younger JSCBs have more concentrated branches and more focused on their business in the central inland provinces.[10] Through Panel A, I can see a significant increase in JSCBs' market share in the central provinces.

As of 2015, there are 130 CCBs with a total of 17,291 branches. Most CCBs were restructured from urban credit cooperatives. Their branches are highly concentrated in the provinces where the banks are headquartered.

[8] In order to scientifically reflect the social and economic development of different regions, the National Bureau of Statistics (NBS) proposes to divide China into four major economic regions. The eastern economic zone includes Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong and Hainan. The north-eastern economic zone includes Liaoning, Jilin and Heilongjiang. The central economic zone includes Shanxi, Anhui, Jiangxi, Henan, Hubei and Hunan. The western economic zone includes Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang.

[9] The six SOCBs in descending order of total assets in 2015 are the Industrial and Commercial Bank of China (ICBC), China Construction Bank (CCB), Agricultural Bank of China (ABC), Bank of China (BOC), Postal Savings Bank of China (PSBC), and Bank of Communications (BOCOM). ICBC, CCB, ABC and BOC are also known as China's "*Big Four*" banks.

[10] According to the statistics of Li et al. (2014), China CITIC Bank, China Merchants Bank, China Everbright Bank, China Minsheng Bank, and Huaxia Bank have more branches across the country, and these five JSCBs are more focused on nationwide growth. The branches of China Guangfa Bank and Shanghai Pudong Development Bank are more concentrated in Guangzhou and Shanghai and their surrounding provinces, respectively (eastern China). As the youngest entrants, Hengfeng Bank and China Zheshang Bank established most of their branches (outside the province where they are headquartered) in Hubei province, Sichuan Province, and Chongqing City (central China).

Like JSCBs, Panel A shows that market share of CCBs increases nationwide. Panel B and Panel C show that CCBs have a relatively even market share across the economic zones during the study period.

I do not include foreign banks in my analysis as they only have a tiny market share in the most developed cities. Their presence only causes negligible influence on the value of competition indices of several eastern provinces. I also exclude rural commercial banks and rural credit cooperatives as their market share is also small; it is also unclear whether they provide loans to non-agricultural SMEs and consumers.

Following the literature of relevant empirical studies, I construct quarterly competition indices of provincial banking markets, *HHI* and *CRn*, based on data of bank branches. A common measurement of the banking market competition is the Herfindahl-Hirschman Index and the concentration ratio of banks in total assets, deposits, loans, or the number of branches (e.g., see Petersen and Rajan, 1995; Corvoisier and Gropp, 2002; Cetorelli, 2004; Degryse et al., 2009). Branch-related events or policies are sometimes used to indicate changes in regional banking competition (Stiroh and Strahan, 2003; Cetorelli and Strahan, 2006; Rice and Strahan, 2010). As province-level operation data of China's commercial banks are not usually available to the public, I cannot calculate the market share of banks in assets, loans, or deposits in most provinces. This obstacle also makes the construction of other proxies such as the Lerner index (Lerner, 1934; Beck et al., 2013; Jiménez et al., 2013) and the "H statistic" (Panzar and Rosse, 1987; Bikker and Haaf, 2002) infeasible. More importantly, unlike the Herfindahl-Hirschman Index and concentration ratio, the Lerner index and the "H statistics" are firm-specific measures of market power instead of region-specific measures of competition. Discussing whether local borrowers are specifically influenced by a certain bank is not the focus of this study as I link banking markets and lending marketplaces by region. I find that most studies focusing on local banking market competition in China rely on branch-based proxies (e.g., see Chong et al., 2013; Ye et al., 2019). Nevertheless, in Section 3.6.4, I calculate the competition indices based on total assets, total deposits, and total loans of banks in data-accessible provinces. I define the difference of *HHI* and *CRn* as:

$$HHI = \sum_{k=1}^{K_{it}} (\#branch_k / \sum_{k=1}^{K_{it}} \#branch_k)^2 \qquad (1)$$

$$CRn = \sum_{m=1}^{n} (\#branch_m) / \sum_{k=1}^{K_{it}} \#branch_k \quad (2)$$

where K_{it} is the number of bank brands in province i during quarter t, and m = 1, 2, 3,… n is the mth largest bank by number of bank branches.

Figure 3 shows the variation in *HHI* across provinces over time. The banking markets of most provinces became significantly more competitive during the study period. The banking markets of provinces in the eastern economic zone are, on average, more competitive than markets of provinces in the central and western economic zones.

Figure 3: Dynamic Banking Competition of Representative Provinces

Figure 3 shows the dynamic banking competition (*HHI*) of representative provinces during the study period. Green, yellow, purple, and red trend lines refer to the dynamic *HHI* of provinces in the eastern, central, north-eastern, and western economic zone, respectively. I only include representative provinces as (i) some trend lines will be highly overlapped and make the whole graph less readable if all provinces are shown; (ii) the most undeveloped provinces, such as Tibet, have significantly higher *HHI* than other provinces and will alter the scale of the graph making trend lines of most provinces difficult to read.

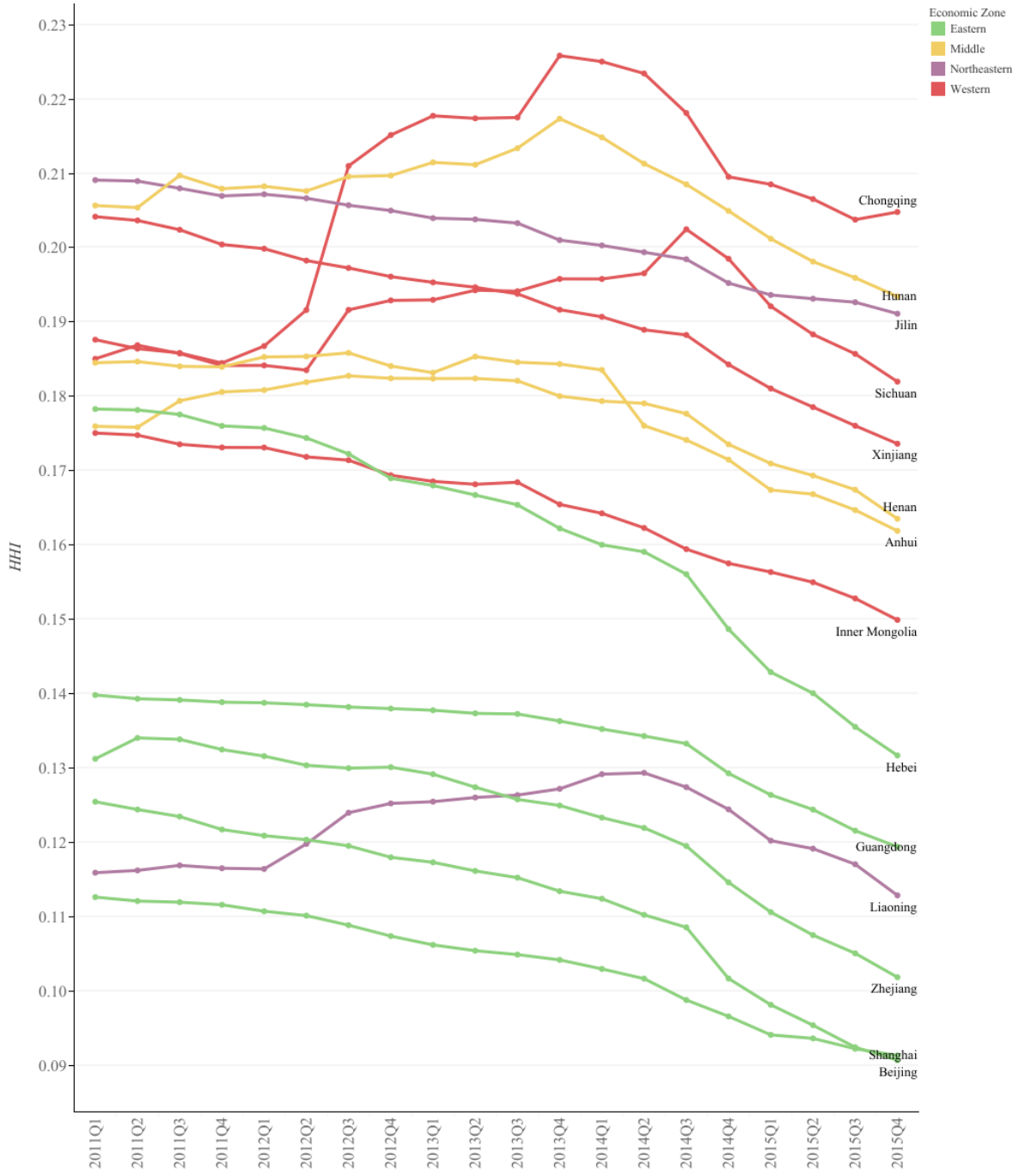


Table 1: Geographical Market Share of Commercial Banks

Panel A reports the provincial market share of SOCBs, JSCBs, and CCBs at the end of 2010 and 2015, respectively. Darker colours represent a higher market share. Red represents the market share of SOCBs, ranging from 70% (light red) to 100% (dark red). Blue represents the market share of JSCBs, ranging from 0% (light blue) to 17% (darker blue). Green represents the market share of CCBs range from 0% (light green) to 19% (dark green). Due to unavailability of data, I grey out Hong Kong, Macao, and Taiwan. Panel B and Panel C report the average market share of SOCBs, JSCBs, and CCBs in the eastern economic zone, the north-eastern economic zone, the central economic zone, and the western economic zone at the end of 2010 and 2015, respectively.

	SOCBs	JSCBs	CCBs
Panel A. Provincial Market Shares			
2010			
2015			
Panel B. Average Market Share of Each Bank Type by Economic Zone (2010)			
East	84.43%	8.57%	7.00%
Northeast	90.73%	2.69%	6.58%
Central	91.16%	2.10%	6.74%
West	84.55%	2.66%	12.79%
Panel C. Average Market Share of Each Bank Type by Economic Zone (2015)			
East	74.38%	15.53%	10.09%
Northeast	80.28%	6.21%	13.51%
Central	82.32%	7.56%	10.12%
West	83.94%	5.89%	10.17%

3.4.2 Variables of Interest and Control Variables

I first obtain information on the funding outcome of every loan application (*Success*), the loan size requested (*Amount*), the loan maturity in months (*Maturity*), the risk premium of a loan over the benchmark lending rate[11] (*Spread*), the number of bidders for a loan (*Bidders*), and the proportion (subscription ratio) of the total requested amount bid by these bidders (*Fraction*) from RRD and the National Internet Finance Association of China[12] (NIFA). Data are collected using self-designed web spiders with technical details shown in Appendix II. I then calculate the length of the text statement from a borrower on RRD (*Words*). For each fully funded (successful) loan, I collect the number of times a borrower on RRD is overdue paying the monthly instalments (*Overdue*) and the information regarding whether the borrower eventually defaults (*Default*).

I obtain the name, ID, telephone number, age, gender, province of residence, marital status, income range, education level, work experience, real estate ownership status, and mortgage status of each borrower. I also use *GDP per capita* to control for economic environments across provinces. Following Rajan and Zingales (1998), I control for financial development across provinces using the ratio of total new loans originated by financial institutions to provincial GDP.

Appendix III includes detailed definitions for each variable. These variables are categorised into (1) loan application characteristics, (2) borrower demographic characteristics, and (3) provincial environment. Table 2 shows the summary statistics for my main variables.

3.4.3 Summary Statistics

My sample is composed of 608,407 records of loan applications on RRD from 2011 to 2015. Panel A of Table 2 shows that 215,985 applications (35.5% of applications) are successful and

[11] The benchmark lending rate is a series of guiding rates, conditional on maturities, issued by the People's Bank of China (PBC). The actual commercial loan rates set by qualified financial institutions are allowed to fluctuate within a certain range around the benchmark interest rate.

[12] NIFA was a self-regulation institution established and organised by the government of China, which provided and updated authoritative information about China's internet finance.

fully funded. The requested loan amounts vary significantly from 1,000 RMB to 1 million RMB. On average, the loan rate of various maturities is 7.43% higher than the benchmark lending rate, with a variation of –3.1% to + 18.55% around the benchmark lending rate. This loan rate set by RRD is not aggressively higher than some credit products offered by China's commercial banks, for example, credit cards.[13] The loan maturity has an average of approximately 20 months and varies from 1 month to 48 months, and 60.54% of applications request a loan longer than 12 months. The bidder structure also varies considerably across loans. On average, a loan has 19.44 bidders, ranging from 0 bidders to 2384 bidders. Finally, among successful applications, the average overdue rate is 0.553, ranging from 0 to 54 times; approximately 1.8% loans result in default.

Panel B reports the summary statistics of borrower characteristics. Overall, more borrowers active on the platform are young, male (81.4%), married (56.8%), less educated (77.4%), and lack working experience (71.7%). The median income level of borrowers is less than 10,000 RMB per month. Only 46.3% of borrowers own a house, and 21.3% of borrowers report having a home loan.

[13] PBC sets the lower and upper limits on the overdraft interest rate of credit cards. The lower (upper) limit of the daily overdraft interest rate is 0.035% (0.05%). Since China's commercial banks typically adopt simple interest rather than compound interest, the annual percentage rate is between 12.775% and 18.25%.

Table 2: Summary Statistics

Panel A of Table 2 reports the summary statistics of loan application characteristics. Panel B reports the summary statistics of demographic characteristics of borrowers. Panel C reports the summary statistics of banking competition indices and those of the economic and financial variables. For variable definitions and details of their construction, see Appendix III.

Variable	Min.	Mean	Med.	Max.	Std. Dev.	N
Panel A. Characteristics of Application Records						
Success	0	0.355	0	1	0.479	608,407
Fraction	0	0.365	0	1	0.481	608,407
Amount	0.1	6.183	4.75	100	8.094	608,407
Maturity	1	19.99	24	48	10.974	608,407
Spread	–3.1	7.43	7	18.55	2.557	608,407
Words	1	213.111	171	1000	164.896	608,407
Bidders	0	19.443	0	2384	48.751	608,407
Overdue	0	0.553	0	54	2.816	215,985
Default	0	0.018	0	1	0.131	215,985
Panel B. Borrowers' Demographic Characteristics						
Age	18	31.584	30	70	7.883	608,407
Gender	0	0.186	0	1	0.389	608,407
Education	1	1.899	2	4	0.774	608,363
High Edu.	0	0.226	0	1	0.418	608,363
Marriage	0	0.568	1	1	0.495	608,407
Income	1	3.113	3	6	1.175	608,403
High Inc.	0	0.288	0	1	0.453	608,403
Work Exp.	1	2.093	2	4	1.053	608,167
High Exp.	0	0.283	0	1	0.451	608,167
House	0	0.463	0	1	0.499	608,407
Home Loan	0	0.213	0	1	0.409	608,407
Panel C. Provincial Variables						
HHI	0.091	0.190	0.179	0.738	0.103	620
CR3	0.421	0.634	0.648	0.958	0.095	620
CR6	0.666	0.881	0.894	1	0.689	620
FinDev	–0.045	0.185	0.147	3.534	0.184	155
GDP per capita	2.434	11.615	9.863	32.338	5.734	620

3.4.4 Research Design

In order to test the *Hypotheses*, I model the effect of banking competition on the marketplace borrowers' probability of being creditworthy through both a linear and a nonlinear specification:

$$Creditworthiness\ Measures_i = \beta_0 + \beta_1 Competition\ Indices_i + \sum_l \gamma_l\, Borrower\ Characteristics_i + \sum_m \delta_m\, Loan\ Characteristics_i + \sum_n \delta_n\, Provincial\ Controls_i + u_i \quad (3)$$

$$P(Creditworthiness\ Measures_i = 1) = \Phi(\beta_0 + \beta_1 Competition\ Indices_i + \sum_l \gamma_l\, Borrower\ Characteristics_i + \sum_m \delta_m\, Loan\ Characteristics_i + \sum_n \delta_n\, Provincial\ Controls_i + u_i) \quad (4)$$

Inspired by Hasan et al. (2022), I adopt both ex-ante and ex-post measures of creditworthiness. Ex-ante measures of creditworthiness include *Success*, *Fraction*, and *Bidders*, which reflect the perceived creditworthiness; ex-post measures of creditworthiness include *Default* and *Overdue*, which measure the actual creditworthiness.[14] I use the linear (probit) regression model if the dependent variable is a continuous variable (binary outcome).

[14] Among these five measures, I treat *Bidders* and *Default* as auxiliary measures serving for the purpose of a robustness check. The reason is that their effectiveness is relatively controversial. For *Bidders*, it may positively predict the creditworthiness as ownership diversification may result from rational herding (Zhang and Liu, 2012). However, irrational herding may also contribute to the ownership diversification in the meantime, which makes *Bidders* a less representative proxy variable of creditworthiness. Compared with *Overdue*, *Default* is a lagging measure of creditworthiness. Since both borrowers' creditworthiness and the level of competition may moderately change along with their repayments, it is a less effective variable in reflecting the creditworthiness and banking market status when they applied for the loan on RRD. Thus, although regressions of five measures show consistent results in the main tests, I do not employ *Bidders* and *Default* in the following tests as their lower effectiveness may distort the results of further analyses.

Competition Indices, i.e., *HHI* and *CRn*, measure the level of banking competition of borrower *i*'s home province. If bank loans are given priority in the pecking order of borrowers, I would observe *HHI* and *CRn* have statistically significant coefficients; otherwise, I would not. Following Hasan et al. (2022), *Borrower Characteristics* are a set of variables controlling for borrower *i*'s characteristics, including *Age*, *Gender*, *Education*, *Marriage*, *Income*, *House*, *Home Loan*, and work experience (*Work Exp.*); *Loan Characteristics* are a set of variables controlling for the loan's characteristics, including *Spread* and *Words*. *Provincial Controls* include *GDP per capita* and financial development (*FinDev*). The way I control for the characteristics of borrowers and loans is also consistent with the literature (e.g., see Stiglitz and Weiss, 1981; Powell and Ansic, 1997; Herzenstein et al., 2011; Pera et al., 2016; Dorfleitner et al., 2016; Chen et al., 2017; Lin et al., 2017; Chen, X. et al., 2018).

I design three heterogeneity tests to see whether some necessary conditions are met if my proposition, i.e., information asymmetry and adverse selection contribute to relaxed screening standards and inclusive banking markets, is true. I also run panel data regressions through clustering marketplace data by province and quarter. These panel data regressions provide results aggregated at the province level. These results suggest the interagency migration of borrowers.

I employ several robustness tests to answer whether the baseline models based on large samples are subject to a Type I error (Section 3.6.1) and tackle potential endogeneity. Provincial banking competition is clearly not randomly assigned, nor is it a choice. Accordingly, I treat banking competition of one's home province as historically and economically inherited. I can safely dismiss the threat from reverse causality as: (i) the marketplace lending industry in China is negligibly small compared to the banking sector, and (ii) each micro-economic transaction is clearly too small to influence the macro economy of a province. Hence, the main identification challenge is not reverse causality, but whether my banking competition indices are correlated

with other (omitted) factors that simultaneously affect the funding outcomes and the performance of loans. In Section 3.6.2, I develop a Difference-in-Differences (DID) strategy to identify the impact of increased banking competition. In Section 3.6.3, I find two instrumental variables and use two-stage least squares (2SLS) regressions to avoid the omitted variable bias. In Section 3.6.4, I build alternative measures of the level of banking competition based on total provincial assets, total provincial deposits, and total provincial loans of banks, and rerun regressions on subsamples. Section 3.6.5 is designed to avoid the errors-in-variables bias. In Section 3.6.6, I account for potential selection bias and show that my study has some external validity by rerunning my baseline models on data from another leading marketplace.

3.5 Empirical Results and Explanations

3.5.1 Main Results

I first test how banking competition (*HHI*) in the home provinces of borrowers affects their probability of being creditworthy. I then test whether my results are sensitive to the way I measure banking competition by replacing *HHI* with *CR3* and *CR6*.

Table 3 reports the effect of banking competition in the home provinces of borrowers on loan funding success (*Success*), the proportion of subscription for a loan (*Fraction*), the number of bidders for a loan (*Bidders*), the overdue times along with the repayments (*Overdue*), and the loan outcome (*Default*). I run probit regressions for *Success* and *Default* and run OLS regressions for other dependent variables. My models control for a full set of borrower characteristics, loan characteristics, and the economic environments of the home provinces of borrowers.

Column 1 of Panel A shows that *HHI* positively predicts the probability that an application is fully funded. To understand the marginal effect, holding all else at the mean level, *HHI*

increasing from 0 to its mean will, on average, result in an 8.10 percentage point rise in the chance of being fully funded, which amounts to 22.81% of the average chance of *Success*. Other columns show qualitatively consistent results: all else being equal, *HHI* increasing from 0 to its mean will, on average: (i) result in a 5.49 percentage point rise in subscription ratio, or 15.05% of the average of *Fraction*; (ii) attract 4.83 more bidders, or 24.83% of the average of *Bidders*; (iii) result in a 0.49 percentage point reduction in the chance of *Default*, or 27.09% of the average chance of *Default* among successful loans; and (iv) lead to being overdue 0.44 fewer times, or 79.29% of the average value of *Overdue* among successful loans. All coefficients discussed above are significant at the 1% confidence level. The consistency of results from ex-ante measures to ex-post measures is likely to rule out the following situations: (i) loans attracting more bidders and subscriptions are largely due to irrational herding; and (ii) most lenders are also aware that borrowers from less competitive banking markets are squeezed out by more stringent lending criteria and show more generalised trust[15] to these borrowers. Both situations will otherwise undermine the effectiveness of my ex-ante measures of creditworthiness.

Most signs of borrower characteristics and loan characteristics show general consistency with my expectations. Female borrowers, borrowers with older age or higher education level, or married borrowers have better funding outcomes and better debt performance. I take note of coefficients of *Home Loan* and *Spread*. The fact that borrowers with home loans have better funding outcomes and better debt performance is consistent with the literature. Lin et al. (2017) propose that borrowers with high debt-to-income ratios may bear higher costs if they are overdue or default on their loans, so they have stronger incentives to maintain their creditworthiness. I also doubt having a home loan is likely to alleviate the information asymmetry between borrowers and lenders. A home loan may signal to lenders that the borrower has passed the credit

[15] Generalised trust refers to the subjective belief in the likelihood that a potential trading partner will perform honestly (Hong et al., 2004; El-Attar and Poschke, 2011; Hasan et al., 2022).

checks of banks, who possess more information about the borrower and are better at credit screening. An application offering a higher rate of interest is associated with a worse funding outcome and worse debt performance. This phenomenon is consistent with the credit rationing theory (Stiglitz and Weiss, 1981). The platform tends to charge high interest to a low-quality borrower with a high default rate. However, raising the interest adversely affects the borrower's capacity to repay the debt, thus further increasing the probability of default. Charging high interest hardly guarantees the profitability of such loans and discourages lenders from investing in them.

Provincial *GDP per capita* is positively and significantly associated with better outcomes and performance. Borrowers from provinces with higher *FinDev* attract more investors on average but are less likely to be fully funded. A possible explanation is that investors may initially show more generalised trust to borrowers from more financially developed areas. However, borrowers excluded by more developed and inclusive financial markets may finally signal to some lenders that their ex-ante creditworthiness is possibly low, so it may be harder for their applications to reach full subscription. In the meantime, where borrowers from higher *FinDev* provinces are fully funded, they show systematically better debt performance. The reason may be that borrowers from more developed and inclusive financial markets may bear higher costs if they default and thus have more motivation for maintaining good repayment records.

Panel B shows the results using alternative measures of the level of provincial banking competition while keeping the same full set of control variables. All columns show results that are significant and consistent with Panel A, indicating that my results are insensitive to how I calculate the branch-based indices of banking competition.

Table 3: Main Results

Table 3 presents the results of regressions on ex-ante measures of creditworthiness, *Success*, *Fraction*, and *Bidders*, and ex-post measures of creditworthiness, *Default*, and *Overdue*, as well as a set of control variables of application characteristics, borrower characteristics, and provincial environments. Year dummies or quarter dummies are also included.[16] Panel A reports the results for *HHI*. Columns (1) and (4) use a probit model. Columns (2), (3) and (5) use OLS regressions. Panel B reports the results for *CR3* and *CR6*. The setting of control variables is the same as Panel A but is not reported. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. For variable definitions and details of their construction, see Appendix III.

Panel A. HHI

	Ex-Ante Measures			*Ex-Post Measures*	
	Success	*Fraction*	*Bidders*	*Default*	*Overdue*
	(1)	(2)	(3)	(4)	(5)
HHI	1.965***	0.359***	31.555***	–1.739***	–2.866***
	(0.076)	(0.017)	(2.095)	(0.391)	(0.250)
Age	0.055***	0.013***	0.923***	–0.002	–0.019***
	(0.000)	(0.000)	(0.010)	(0.001)	(0.001)
Gender	0.281***	0.070***	6.667***	–0.251***	–0.243***
	(0.005)	(0.012)	(0.173)	(0.022)	(0.010)
High Edu.	0.139***	0.017***	2.588***	–0.321***	–0.139***
	(0.005)	(0.001)	(0.151)	(0.021)	(0.013)
Marriage	0.245***	0.053***	2.237***	–0.142***	–0.116***
	(0.005)	(0.001)	(0.119)	(0.018)	(0.013)
High Inc.	–0.006	–0.008***	4.316***	0.217***	0.262***
	(0.005)	(0.001)	(0.143)	(0.017)	(0.013)
High Exp.	–0.624***	–0.161***	–11.683***	0.611***	1.117***
	(0.006)	(0.001)	(0.112)	(0.025)	(0.026)
House	–0.219***	–0.037***	–0.296**	0.109***	0.164***

[16] I use year dummies in Column (1) of Panel A and Columns (1)–(2) of Panel B. The reason is that the sample size is too big, and the model would be too complicated if I use quarter dummies for a nonlinear estimation to reach convergence by the software. It is based on the same reason that models in the following tables hire year dummies.

	(0.006)	(0.001)	(0.126)	(0.020)	(0.021)
Home Loan	0.777***	0.215***	14.444***	–0.556***	–0.802***
	(0.006)	(0.001)	(0.195)	(0.024)	(0.021)
Spread	–0.223***	–0.030***	–1.234***	0.234***	0.484***
	(0.002)	(0.000)	(0.013)	(0.008)	(0.015)
Words	0.005***	0.001***	0.054***	–0.004***	–0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GDP per capita	0.026***	0.005***	0.224***	–0.020***	–0.023***
	(0.000)	(0.000)	(0.017)	(0.000)	(0.000)
FinDev	–0.820***	0.005	1.417*	–0.703**	–0.568***
	(0.028)	(0.007)	(0.747)	(0.143)	(0.080)

Table continued…

Time Dummies	Year	Quarter	Quarter	Quarter	Quarter
No. of Obs.	608,407	608,407	608,407	215,985	215,985
Adj. R^2		0.4717	0.2395		0.1464
Pseudo R^2	0.4527			0.2989	

Panel B. CR3 and CR6

	Ex-Ante Measures					
	Success		*Fraction*		*Bidders*	
	(1)	(2)	(3)	(4)	(5)	(6)
CR3	1.876***		0.387***		33.058***	
	(0.053)		(0.011)		(1.508)	
CR6		1.708***		0.407***		36.301***
		(0.051)		(0.011)		(1.528)
Borrower Characteristics	Yes	Yes	Yes	Yes	Yes	Yes

Loan Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Provincial Variables	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Year	Year	Quarter	Quarter	Quarter	Quarter
No. of Obs.	608,407	608,407	608,407	608,407	608,407	608,407
Adj. R^2			0.4723	0.4724	0.2398	0.2400
Pseudo R^2	0.4535	0.4533				

	Ex-Post Measures			
	Default		*Overdue*	
	(7)	(8)	(9)	(10)
CR3	–1.115***		–2.106***	
	(0.233)		(0.163)	
CR6		–0.946***		–1.636***
		(0.205)		(0.138)
Borrower Characteristics	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes
Provincial Variables	Yes	Yes	Yes	Yes
Time Dummies	Quarter	Quarter	Quarter	Quarter
No. of Obs.	215,985	215,985	215,985	215,985
Adj. R^2			0.1466	0.1464
Pseudo R^2	0.2990	0.2989		

3.5.2 Heterogeneity Tests

3.5.2.1 Heterogeneous Effects from Banks

If my proposition is true, banks in areas of greater competition reallocate credit to low-quality borrowers because of greater information asymmetry. A prediction in line with Sharpe (1990) and Marquez (2002) is that when entrants (new banks) contribute more competition to the banking market, credit reallocation due to competition would be theoretically more pronounced. Table 1 shows that from 2010 to 2015, SOCBs dominated every local market even though their overall market share declined. SOCBs tend to be incumbents in local markets as significantly more local borrowers are informationally captured by them. By contrast, the market share of JSCBs and CCBs are much smaller but growing quickly. As discussed in Section 3.4.1, JSCBs are rapidly expanding inland from the eastern coastal areas. Table 1 also illustrates that the presence of JSCBs more than doubled in 5 years in the north-eastern, central, and western economic zones. Thus, compared with SOCBs, they operate more like entrants given their informational disadvantage.[17] With the stronger presence of these entrants and borrower turnover[18], borrower information becomes more dispersed and the space for adverse selection increases. As a result, competition by JSCBs and CCBs makes the credit allocation further shift toward less creditworthy borrowers. To test the possible heterogeneous effects from banks, I interact banking competition with the market share of JSCBs and CCBs. I define the market share of JSCBs as *MSJSCB* and of CCBs as *MSCCB*:

$$MSJSCB = \sum_{j=1}^{J_{it}} (\#branch_j) / \sum_{k=1}^{K_{it}} \#branch_k \qquad (5)$$

[17] Allen et al. (2012) also treat some China's domestic and foreign banks besides the "big four" banks as market entrants.

[18] According to the definition of Marquez (2002), borrower turnover refers to the rate at which pre-existing borrowers leave the credit market and the rate at which new borrowers enter the credit market. He finds that high turnover of borrowers erodes the informational advantages of incumbents.

$$MSCCB = \sum_{j=1}^{C_{it}} (\#branch_c) / \sum_{k=1}^{K_{it}} \#branch_k \qquad (6)$$

where J_{it} is the number of JSCBs brands in province i during quarter t, and C_{it} is the number of CCBs brands in province i during quarter t.

Panel A of Table 4 reports the heterogeneous effects of competition contributed by JSCBs and CCBs. The results show that the competition provided by JSCBs and CCBs significantly and consistently enhances the marginal effect of *HHI*. As banking competition increases (*HHI* decreases), the creditworthiness of borrowers who rely on lending marketplaces deteriorates. This trend is further enhanced by the stronger presence of JSCBs and CCBs. In other words, the stronger presence of JSCBs and CCBs helps further reallocate bank credit toward low-quality borrowers and demotivates their migration to lending marketplaces. The results are consistent with the theory proposed by Sharpe (1990) and Marquez (2002).

However, although Panel A shows that the competition by JSCBs and CCBs plays a role, it is not necessarily due to information dispersion and adverse selection. Another possible explanation is that SOCBs, JSCBs, and CCBs have different efficiencies and performances (as discussed in Section 3.2.1) and different emphases on their business of personal loans, which necessitates other tests.

3.5.2.2 Heterogeneous Impacts on Borrowers of Different Ages

If my proposition is true, another prediction would be that younger borrowers benefit more from the enhanced banking competition. Unlike the credit review of firms, banks review the creditworthiness of consumers based on their debt performance and assessment of their current and future income. Younger borrowers generally have shorter histories of debt performance, more uncertainty in relation to future income, and a higher degree of turnover than older

borrowers, so they are less informationally captured by banks. If the theory of Sharpe (1990) and Marquez (2002) is right, credit reallocation to younger borrowers would be more significant as the ability of banks to screen out younger and low-quality borrowers reduces to a greater extent.

Panel B of Table 4 reports the heterogeneous effects of banking competition on younger and older borrowers. I define *Young* as a dummy variable that equals 1 if borrowers are under 30 years old (the median age of my sample) when applying for loans and interact *Young* with *HHI*. For younger marketplace borrowers, the marginal effect of *HHI* is significantly and consistently higher. As banking competition increases (*HHI* decreases), the creditworthiness of younger borrowers who rely on marketplaces decreases to a greater extent than that of older borrowers. Compared with older borrowers, the ability of banks to screen out younger and unqualified borrowers further deteriorates, so younger borrowers are less likely to rely on marketplaces except those who cannot pass the further relaxed credit checks. In other words, younger borrowers benefit more from greater competition. The results are also consistent with the theory proposed by Sharpe (1990) and Marquez (2002).

3.5.2.3 Newcomers or New Personalities?

If my proposition is true, then financially constrained borrowers migrate to marketplaces. However, what if banking competition is associated with the creditworthiness of borrowers just because it helps to build their creditworthiness or other new personalities? In such a situation, the association between banking competition and creditworthiness still exists even if interagency migration does not occur; and banking competition would play a role similar to *Age*, *Gender*, *Marriage,* or other borrower characteristics in determining creditworthiness. I have not found relevant studies that discuss the relationship between dynamic banking competition and the development of new personalities, and theoretically, such a relationship is not likely to exist. Nevertheless, I still design a test. I employ a new variable, *ApplicationNum*, which refers to the

number of applications a borrower has listed on RRD before. I use this variable to reflect how "new" a borrower is to the marketplace and interact *ApplicationNum* with *HHI*. If interagency migration does occur, these migrants become marketplace newcomers. The effect size of banking competition on the creditworthiness of these newcomers should be significantly larger than pre-existing borrowers. Otherwise, I should not observe significant heterogeneity of effect sizes among all borrowers.

Panel C of Table 4 shows that the coefficients of interaction terms are consistent and significant across the models. As borrowers list more applications on the marketplace, the marginal effect of *HHI* on their funding outcomes and debt performance significantly diminishes. The results show that marketplace newcomers are significantly more affected by the banking competition of their home province than pre-existing marketplace customers are, which is consistent with my proposition that interagency migration occurs.

Table 4: Heterogeneous Effects from Banks

In Panel A of Table 4, I rerun regressions by interacting *HHI* with the market share of JSCBs and CCBs. In Panel B, I rerun regressions by interacting *HHI* with a dummy variable, *Young*. Borrowers are classified as young borrowers if they are under 30 years old (the median age of my sample). In Panel C, I rerun regressions by interacting *HHI* with *ApplicationNum*. *ApplicationNum* refers to the number of applications a borrower has listed previously on RRD. Column (1) of each panel uses a probit model. All other columns use OLS regressions. Application characteristics, borrower characteristics, and provincial environments are controlled. Year dummies or quarter dummies are also included. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. For variable definitions and details of their construction, see Appendix III.

Panel A. Heterogeneous Effects from Banks

	Ex-Ante Measures		*Ex-Post Measure*
	Success	*Fraction*	*Overdue*
	(1)	(2)	(3)
HHI	2.458***	0.509***	–3.142***
	(0.079)	(0.018)	(0.250)
HHI × *MSJSCB*	21.382***	5.124***	–15.045***
	(0.863)	(0.187)	(2.173)
HHI × *MSCCB*	21.288***	4.604***	–4.985***
	(0.710)	(0.150)	(2.040)
Borrower Characteristics	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes
Provincial Variables	Yes	Yes	Yes
Time Dummies	Year	Quarter	Quarter
No. of Obs.	608,407	608,407	215,985
Adj. R^2		0.4726	0.1467
Pseudo R^2	0.4539		

Table continued…

Panel B. Heterogeneous Effects on Young versus Elder Borrowers

	Ex-Ante Measures		*Ex-Post Measure*
	Success	*Fraction*	*Overdue*
	(1)	(2)	(3)
HHI	1.775***	0.311***	–2.358***
	(0.079)	(0.017)	(0.262)
HHI × Young	0.400***	0.119***	–0.727***
	(0.042)	(0.009)	(0.120)
Borrower Characteristics	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes
Provincial Variables	Yes	Yes	Yes
Time Dummies	Year	Quarter	Quarter
No. of Obs.	608,407	608,407	215,985
Adj. R^2		0.4719	0.1466
Pseudo R^2	0.4528		

Panel C. Newcomers or New Personalities

	Ex-Ante Measures		*Ex-Post Measure*
	Success	*Fraction*	*Overdue*
	(1)	(2)	(3)
HHI	2.365***	0.519***	–3.700***
	(0.079)	(0.018)	(0.244)
HHI × ApplicationNum	–0.132***	–0.044***	0.631***
	(0.007)	(0.002)	(0.028)
Borrower Characteristics	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes
Provincial Variables	Yes	Yes	Yes
Time Dummies	Year	Quarter	Quarter
No. of Obs.	608,407	608,407	215,985
Adj. R^2		0.4747	0.1643
Pseudo R^2	0.4550		

3.5.3 Panel Data Evidence

If interagency migration of borrowers does occur in an expected way, holding other factors constant I should observe that the volume of applications increases in a less competitive market. I provide aggregate-level evidence where data are clustered by provinces and quarters. I employ three measures of the application volume: province-level total borrowers (*PTB*), province-level total loan numbers (*PTLN*), and province-level total loan amounts (*PTLA*). I control for *Population*, *GDP*, and *FinDev*.

Results in Table 5 show consistency with the idea that interagency migration occurs. A less competitive banking market (higher *HHI*) is associated with more marketplace borrowers, more marketplace loans requested, and larger total amounts requested. The signs of the control variables are consistent with my expectations. I take note of coefficients of *Population*. Descriptive statistics show that more marketplace borrowers are from financially developed areas where the banking markets are more competitive overall. This phenomenon seems to conflict with the idea that banking competition promotes financial inclusion. These significant and positive coefficients of *Population* across columns indicate that the larger number of marketplace borrowers in financially developed areas is mainly due to the bigger population base of these areas. Once the population is controlled for, the regional banking competition (concentration) negatively (positively) predicts the application volume in the marketplace, which is consistent with my proposition on interagency migration of borrowers.

Table 5: Panel Data Evidence

Table 5 reports regressions on panel data clustered by provinces and quarters. The dependent variable is application volume. Application volume is measured by province-level total borrowers (*PTB*), province-level total loan numbers (*PTLN*), and province-level total loan amounts (*PTLA*). Provincial environments are controlled. Quarter and province fixed effects are included. Standard errors are clustered at the province level and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. For variable definitions and details of their construction, see Appendix III.

	PTB	*PTLN*	*PTLA*
	(1)	(2)	(3)
HHI	0.0013**	0.0015**	0.0008*
	(0.0006)	(0.0008)	(0.0005)
Population	0.0048***	0.0062***	0.0037***
	(0.0007)	(0.0009)	(0.0004)
GDP	0.0002***	0.0002***	0.0001***
	(0.0000)	(0.0000)	(0.0000)
FinDev	–0.012	–0.023	–0.017
	(0.077)	(0.091)	(0.056)
Quarter Fixed Effects	Yes	Yes	Yes
Province Fixed Effects	Yes	Yes	Yes
No. of Obs.	620	620	620
R^2	0.8060	0.8127	0.8255

3.6 Robustness Tests

3.6.1 Are Large Samples Problematic?

My baseline models use two samples containing 608,407 and 215,985 observations. Hypothesis testing using such large samples may raise the probability of a Type I error. Following Hasan et al. (2022), I implement a bootstrapping method to check the robustness of my findings. Specifically, I draw subsamples with replacement that contain one-tenth as many observations as the original samples and repeat my regression analysis for this subsample. I then replicate this procedure 1,000 times and calculate the bootstrap statistics. Table 6 shows that my results and their significance are qualitatively unchanged; that is, regional banking competition is

negatively and significantly correlated with the creditworthiness of borrowers relying on lending marketplaces even when samples are substantially smaller. In Section 3.6.2, I conduct two DID tests that also involve substantially smaller subsamples and obtain consistent results.

Table 6: Bootstrapping

Table 6 reports the results of regressions on ex-ante measures of creditworthiness *Success* and *Fraction* and ex-post measure of creditworthiness *Overdue* using a bootstrapping method. Columns (1)–(3) use probit models. Columns (4)–(9) use OLS regressions. Application characteristics, borrower characteristics and provincial environments are controlled. Year dummies or quarter dummies are also included. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. For variable definitions and details of their construction, see Appendix III.

	Ex-Ante Measures						*Ex-Post Measures*		
	Success			*Fraction*			*Overdue*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
HHI	1.965***			0.359***			–2.866***		
	(0.239)			(0.053)			(0.800)		
CR3		1.876***			0.387***			-2.106***	
		(0.167)			(0.036)			(0.470)	
CR6			1.708***			0.407***			-1.636***
			(0.167)			(0.034)			(0.438)
Borrower Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provincial Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Year	Year	Year	Quarter	Quarter	Quarter	Quarter	Quarter	Quarter
No. of Obs. in the Original Sample	608,407	608,407	608,407	608,407	608,407	608,407	215,985	215,985	215,985
No. of Obs. in Subsamples	60,840	60,840	60,840	60,840	60,840	60,840	21,598	21,598	21,598
Repeat Times	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000
Adj. R^2				0.4717	0.4723	0.4724	0.1464	0.1466	0.1464
Pseudo R^2	0.4527	0.4535	0.4533						

3.6.2 Banking Competition or Other Economic Factors?

The banking sector in China is deeply embedded in the entire economic system. My results would be untenable if they were affected by, for some unknown reasons, other confounders. To avoid the possible confounding impacts of other economic factors, I design a DID method to isolate the influence of banking competition from the entire economic system. Inspired by Chen et al. (2021), the events I choose are the establishments of Zhongyuan Bank in Henan Province and Bank of Gansu in Gansu Province, which are the two most observable establishments of commercial banks in the period I study.[19] Since both Zhongyuan Bank and Bank of Gansu were restructured from small local CCBs and other depository financial institutions, their establishments did not cause sudden growth in local credit supply, which frees me from undesired spill-over effects on the local economy. Instead, their establishments increased banking competition by consolidating previously fragmented market shares and leveraging economies of scale and synergy.

Thus, I conduct my DID tests surrounding the establishments of Zhongyuan Bank (Bank of Gansu) and report the results in Panel A (Panel B) of Table 7. *Henan* and *Gansu* are two dummy variables indicating whether borrowers come from Henan province and Gansu province, respectively. *Post 1* and *Post 2* are two dummy variables indicating whether a loan application on RRD is after the establishments of Zhongyuan Bank and Bank of Gansu, respectively. Further details are listed in Panel E of Appendix III. After controlling for the sole effects of *Henan*

[19] Other commercial banks established from 2011 to 2015 include the Ningbo Commerce Bank and Ningbo Donghai Bank in Zhejiang Province, Jiangxi Bank in Jiangxi Province, Hubei Bank in Hubei Province, Guangdong Huaxing Bank in Guangdong Province, Bank of Hainan in Hainan Province, and Bank of Tibet in Tibet Province. The reasons for not choosing these banks are: (i) these banks were established either at the beginning of or the end of the period I study, and some banks are in provinces with low populations, so I have too few observations before or after their establishments; (ii) some of them only opened branches in several cities in their home provinces, making their establishments less representative and less observable at the provincial level. Nevertheless, I still exclude the application records from these seven provinces to avoid the potential disturbance to my DID results. Further, I exclude loans from Gansu (Henan) when running the DID test on the establishment of Zhongyuan Bank (Bank of Gansu).

(*Gansu*) and *Post 1* (*Post 2*), the coefficients of interaction terms, *Henan * Post 1* and *Gansu * Post 2*, reflect the net effect of the bank establishments. For every measure of the creditworthiness of marketplace borrowers, I run DID regressions on three samples: Scope 1 is a nationwide sample; Scope 2 only contains loans from the tested province and provinces surrounding it; and Scope 3 only contains loans from the tested province and provinces in the same economic zone. Scope 2 and Scope 3 are designed to further mitigate the threat from possible unknown confounders as surrounding provinces and provinces in the same economic zone have similar geographic attributes and economic environments.

The results presented in Table 7 are generally consistent with my expectations. Panel A shows that, after the establishment of Zhongyuan Bank and the increase of local banking competition, borrowers relying on RRD become less creditworthy. Such decreases in creditworthiness are significant and consistent across different measures and different scopes. Panel B reveals a similar pattern after the establishment of Bank of Gansu. One exception is when I use *Fraction* to measure creditworthiness. According to the definitions, *Success* measures the full subscription rate of the loan applications, while *Fraction* measures the subscription ratio of these applications. The results in Panel B mean that the full subscription rate of borrowers from Gansu who list applications after the establishment of Bank of Gansu significantly decreases. In the meantime, their average subscription ratio is not significantly different from other provinces or surrounding provinces; it is significantly higher than provinces in the same economic zone. This inconsistency is likely to be due to the different emphases of these measures on the concept of "creditworthiness". My baseline models have shown that on the nationwide average, these measures are stable and yield consistent results, but their differences in emphases may become observable in some unique situations. Since *Success* is a more stringent measure of creditworthiness than *Fraction*, the results in Panel B show general consistency. Overall, both

the establishments of Zhongyuan Bank and Bank of Gansu are isolated events that solely influence the local banking competition. Still, I further mitigate the threat from potential confounding impacts by narrowing down my sample and comparing the situations of tested provinces with geographically and economically similar provinces. My DID results show that an isolated banking-competition-enhancing event significantly reduces the creditworthiness of borrowers on RRD, which is in line with the baseline models.

Table 7: A DID Identification Strategy

Table 7 reports the results of DID regressions. Panel A reports DID regressions surrounding the establishment of Zhongyuan Bank in Henan Province; Panel B reports DID regressions surrounding the establishment of Bank of Gansu in Gansu Province. For each measure of creditworthiness, I run regression on three scopes: Scope 1 is a nationwide sample; Scope 2 only contains loans from the tested province and provinces surrounding it; Scope 3 only contains loans from the tested province and provinces in the same economic zone. Columns (1)–(3) of each panel use probit models. Columns (4)–(9) use OLS regressions. Application characteristics, borrower characteristics and provincial environments are controlled. Year dummies or quarter dummies are also included. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. For variable definitions and details of their construction, see Appendix III.

Panel A. The Establishment of Zhongyuan Bank

	Success			*Fraction*			*Overdue*		
	Scope 1	Scope 2	Scope 3	Scope 1	Scope 2	Scope 3	Scope 1	Scope 2	Scope 3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Henan	0.183***	0.242***	0.300***	0.047***	0.084***	0.071***	–0.122***	–0.398***	–0.309***
	(0.015)	(0.019)	(0.019)	(0.003)	(0.004)	(0.004)	(0.039)	(0.060)	(0.065)
Post 1	0.772***	0.687***	0.508***	0.387***	0.386***	0.204***	–5.559***	–1.658	–0.320
	(0.025)	(0.055)	(0.072)	(0.010)	(0.022)	(0.027)	(0.958)	(2.347)	(2.953)
*Henan * Post 1*	–0.190***	–0.157***	–0.159***	–0.045***	–0.039***	–0.036***	0.142***	0.162***	0.424***
	(0.021)	(0.023)	(0.024)	(0.004)	(0.005)	(0.005)	(0.052)	(0.058)	(0.072)
Borrower Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provincial Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Year	Year	Year	Quarter	Quarter	Quarter	Quarter	Quarter	Quarter
No. of Obs.	512,217	134,135	87,156	512,217	134,135	87,156	187,580	48,165	25,938
Adj. R^2				0.4779	0.4920	0.4766	0.1453	0.1485	0.1644
Pseudo R^2	0.4627	0.4722	0.4659						

Panel B. The Establishment of Bank of Gansu

	Success			*Fraction*			*Overdue*		
	Scope 1	Scope 2	Scope 3	Scope 1	Scope 2	Scope 3	Scope 1	Scope 2	Scope 3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Gansu	1.110***	1.265***	1.039***	0.095**	0.046	–0.025	–3.739***	–2.926***	–2.072***
	(0.208)	(0.221)	(0.212)	(0.045)	(0.046)	(0.047)	(0.656)	(1.060)	(0.871)
Post 2	0.750***	0.863***	0.629***	0.384***	0.501***	–0.448***	–5.658***	–3.070**	–2.289
	(0.025)	(0.092)	(0.066)	(0.010)	(0.030)	(0.024)	(0.957)	(1.293)	(2.178)
*Gansu * Post 2*	–0.468**	–0.651***	–0.469**	0.023	0.054	0.108**	3.367***	2.734***	1.843**
	(0.209)	(0.222)	(0.212)	(0.044)	(0.046)	(0.047)	(0.657)	(1.055)	(0.868)
Borrower Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provincial Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Year	Year	Year	Quarter	Quarter	Quarter	Quarter	Quarter	Quarter
No. of Obs.	492,972	63,612	107,998	492,972	63,612	107,998	180,696	17,538	35,827
Adj. R^2				0.4778	0.4381	0.4811	0.1453	0.1539	0.1419
Pseudo R^2	0.4617	0.4101	0.4510						

3.6.3 Instrumental Variable Approach

To tackle the potential omitted variable bias, I adopt two instrumental variables. For my study, a qualified instrumental variable would not have independent effects on the dependent variable (funding and repaying outcomes), but through the explanatory variable of interest (banking competition). The first instrumental variable I choose is the average *HHI* of other provinces in the same economic zone (*HHIEZ*). As provinces in the same economic zone have similar geographical, social, and economic environments based on the definition of NBS, and commercial banks use similar operating strategies in provinces within the same economic zone, the competition levels of their banking markets would be positively correlated. However, an administrator of a local bank is unlikely to consider whether the competition of surrounding provinces is fierce or not when granting a loan; individual borrowers are unlikely to bother themselves with borrowing from other provinces either.[20] Thus, I think the average level of competition in other provinces will not independently affect my dependent variables. I take the log form of *HHIEZ* in the following 2SLS regressions. The second instrumental variable I choose is the number of bank brands in a province or *K* in Formula (1). *K* is mathematically correlated with *HHI* according to the construction of the Herfindahl-Hirschman Index. Similarly, neither a local bank administrator nor an individual borrower is likely to make decisions based on *K* without considering the branch quantity of every competing bank.[21] Thus, I think *K* can only affect my dependent variables through *HHI*.

Table 8 reports the results of 2SLS regression based on instrumental variables *log(HHIEZ)* and *K*. Consistent with my predictions, the first-stage results in Panel B show that *log(HHIEZ)* and *K* are significantly correlated with *HHI* in the expected directions. The banking market

[20] Some banks have policies that prohibit borrowers from borrowing personal loans from their branches in other provinces.

[21] Once they consider both *K* and the branch quantity, they are essentially considering *HHI*.

competition of a province is significantly and positively associated with the average banking competition of provinces in the same economic zone. Holding other factors constant, more brands of banks would mean greater competition, i.e., a smaller *HHI*. The second-stage results presented in Panel A validate my baseline results that *HHI* is an important determinant of funding outcomes and debt performance. To test the relevance condition of instrumental variables, I report that the *p*-value of the F statistics for the instruments-only joint significance is 0.000. I implement tests for weak instruments following Stock and Yogo (2005). Panel B reports the critical values for 2SLS at the 10% level. The reported minimum eigenvalue statistics greatly exceed the critical value of 19.93 and are large enough to reject the null hypothesis of weak instruments. To test the exogeneity condition, I conduct an over-identification test as I have two instruments for one possibly endogenous variable. The reported p-values of Hansen-*J* statistics are larger than 10%, so the over-identification restriction is valid.

Table 8: Instrumental Variable Regressions

Panel A and Panel B of Table 8 report the second and first stage results of the instrumental variable regressions, respectively. My first instrument, *HHIEZ*, refers to the average HHI in terms of bank branches in other provinces within the same economic zone. I further choose the log form of *HHIEZ*. The second instrument is *K*, which denotes the number of bank brands in a province. Application characteristics, borrower characteristics, and provincial environments are controlled. Year dummies or quarter dummies are also included. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. For variable definitions and details of their construction, see Appendix III.

	Success	*Fraction*	*Overdue*
	(1)	(2)	(3)
Panel A. Second Stage			
HHI	7.410***	1.658***	–8.552***
	(0.168)	(0.042)	(0.585)
Borrower Characteristics	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes
Provincial Variables	Yes	Yes	Yes
No. of Obs.	608,407	608,407	215,985
Panel B. First Stage			
log(HHIEZ)	0.035***	0.030***	0.036***
	(0.000)	(0.002)	(0.002)
K	–0.001***	–0.001***	–0.001***
	(0.000)	(0.000)	(0.000)
Time Dummies	Year	Quarter	Quarter
Adj. R^2	0.5726	0.5882	0.6715
Partial R^2	0.2100	0.1590	0.2344
F-statistics (*p*-value)	0.000	0.000	0.000
Minimum eigenvalue statistics	80,872.8	57,493.9	33,055.6
Critical value: 10%	19.93	19.93	19.93
Over-identification *J* (*p*-value)	0.5251	0.1035	0.3300

3.6.4 Are Branch-based Competition Indices Representative?

The contribution of my study will be trivial if the conclusion is sensitive to how I measure banking competition. In the main tests, I replace *HHI* with *CR3* and *CR6* and get consistent results; however, they are all based on bank branches. To mitigate the threat of errors-in-variables bias, I calculate the competition indices based on total assets, total deposits, and total loans of banks. Due to data availability, I can only hand collect the provincial total assets of SOCBs, total deposits, and total loans from finance yearbooks of specific provinces.[22] Other supporting data are collected from PBC and the provincial bureau of statistics (PBS).

I report the results in Table 9. Panel A, Panel B, and Panel C report results of regressions on competition indices in terms of total assets, total deposits, and total loans, respectively. Since only details of SOCBs are available, and the "*Big Four*" SOCBs dominate the banking markets of these specific provinces, the explanatory variables I choose are the concentration ratio of the four biggest banks (the "*Big Four*" SOCBs), *TACR4 (/ TDCR4/ TLCR4)*, and the market share of all six SOCBs combined, *TASOCB (/ TDSOCB/ TLSOCB)*. All results are significant in expected directions and consistent with the baseline models. There is no evidence implying that the decisions of provincial governments to disclose the financial positions of SOCBs is relevant to their performance. Provinces disclosing such data are not concentrated in specific regions and have various geographical environments and economic prosperities. Thus, the randomness of samples is ensured. Overall, the results suggest that my baseline models are insensitive to how I measure banking competition.

[22] Specifically, I collect these data from finance yearbooks of Gansu Province, Henan Province, Hubei Province, Shandong Province, Shanghai City, Yunnan Province, and Zhejiang Province. However, not every province discloses all three dimensions (total provincial assets, total provincial deposits, and total provincial loans) of SOCBs. That is why the sample size fluctuates across Table 9.

Table 9: Alternative Measures of Banking Competition

Table 9 reports regressions on alternative measures of banking competition. Panels A, B, and C report the results of regressions on competition indices in terms of total provincial assets, total provincial deposits, and total provincial loans of a bank, respectively. In each panel, I run regressions on the concentration ratio of the four biggest banks (the "*Big Four*" SOCBs) and the market share of all six SOCBs for every creditworthiness measure. Columns (1) and (2) of each panel hire probit models. Columns (3)–(6) use OLS regressions. Application characteristics, borrower characteristics, and provincial environments are controlled. Quarter dummies are also included. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. For variable definitions and details of their construction, see Appendix III.

Panel A. Market Shares in terms of Total Assets

	Success		*Fraction*		*Overdue*	
	1	2	3	4	5	6
TACR4	1.133***		0.279***		–5.402***	
	(0.284)		(0.060)		(0.763)	
TASOCB		4.551***		0.502***		–10.424***
		(0.202)		(0.032)		(0.690)
Borrower Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Provincial Variables	Yes	Yes	Yes	Yes	Yes	Yes
Quarter Dummies	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	153,299	153,299	153,299	160,081	51,688	51,688
Adj. R^2			0.4438	0.4470	0.1630	0.1681
Pseudo R^2	0.4456	0.4485				

Panel B. Market Shares in terms of Total Deposits

	Success		*Fraction*		*Overdue*	
	1	2	3	4	5	6
TDCR4	1.858***		0.404***		–3.697***	
	(0.263)		(0.056)		(0.689)	
TDSOCB		3.376***		0.874***		–4.073***
		(0.162)		(0.035)		(0.360)
Borrower Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Provincial Variables	Yes	Yes	Yes	Yes	Yes	Yes
Quarter Dummies	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	171,801	171,801	171,801	171,801	58,173	58,173

Adj. R^2			0.4443	0.4461	0.1610	0.1619
Pseudo R^2	0.4450	0.4467				

Panel C. Market Shares in terms of Total Loans

	Success		*Fraction*		*Overdue*	
	1	2	3	4	5	6
TLCR4	2.730***		0.684***		–10.954***	
	(0.237)		(0.050)		(0.958)	
TLSOCB		4.976***		1.243***		–17.480***
		(0.412)		(0.086)		(1.706)
Borrower Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Provincial Variables	Yes	Yes	Yes	Yes	Yes	Yes
Quarter Dummies	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	118,417	118,417	118,417	118,417	36,437	36,437
Adj. R^2			0.4367	0.4369	0.1914	0.1909
Pseudo R^2	0.4349	0.4352				

3.6.5 Are Borrowers on RRD Representative?

The contribution of my study will be limited if borrowers on RRD are not representative. In a worse scenario, my conclusion will be threatened by selection bias if the potential uniqueness of RRD borrowers influences their creditworthiness-related response to banking competition of their home province. To show my study has some external validity, and to mitigate the potential threat from selection bias, I rerun my baseline models on data from another lending marketplace of China – Yilongdai (YLD).

YLD is also one of the leading marketplaces in China. I collect 117,190 successful loans from the fourth quarter of 2014 to the fourth quarter of 2015. All these loans belong to a plan named the Yinong Plan, which emphasises the financing of agricultural production. Since only fully funded loans are accessible, I reconstruct three ex-post measures of creditworthiness based on variables provided by the marketplace: the number of times a borrower has successfully borrowed from the marketplace before (*SuccessTimes*); the number of times a borrower has repaid the instalments on time (*RepaidTimes*); the number of times a borrower is overdue (*Overdue*). I control for the same set of loan characteristics, [23] borrower characteristics, and provincial environments as in baseline regressions. I report the results in Table 10. For every measure of creditworthiness, I run regressions on each of three competition indices, *HHI*, *CR3*, and *CR6*. The results show that borrowers on YLD respond to local banking market competition in the same way as borrowers on RRD. As the proportion of borrowers engaged in agricultural production is significantly higher on YLD, I think that the target customer groups of RRD and YLD do not completely overlap. Thus, the results in Table 10 confirm that my study has some external validity when I switch to another platform and to a different group of borrowers. These results also reduce the probability that my analysis is exposed to severe selection bias.

[23] I do not consider controlling for the length of loan descriptions provided by borrowers. I find that the loan descriptions published on the marketplace are highly truncated, so the length of loan descriptions is almost constant.

3.7 Chapter Conclusion and Policy Implications

This chapter examines how China's regional banking market competition influences the use of shadow credit. Using loan-level data from a leading online lending marketplace in China and data on bank branches, I show that regional banking market competition affects the creditworthiness of marketplace borrowers. All else being equal, marketplace borrowers from concentrated banking markets are more likely to be creditworthy than marketplace borrowers from competitive banking markets. Heterogeneity tests show that the association between banking market competition and the creditworthiness of marketplace borrowers is particularly strong when (i) entrants (new banks) contribute more competition to the banking markets; (ii) borrowers are younger; and (iii) borrowers are new to the marketplace. The main empirical results are robust and continue to hold after accounting for potential endogeneity. The empirical results suggest borrowers migrate from the banking sector to the lending marketplace when the banking market is concentrated, and banking competition improves the level of financial inclusion of individuals and households through relaxed credit checks. My results are also consistent with the presence of information asymmetry and information dispersion among the banks.

My study suggests that the government should not only advocate for greater competition in the banking market but also encourage and help non-state commercial banks to gain a higher market share, which is potentially a more effective way to improve financial inclusion. Given the preference of China's borrowers for bank loans, the government should leave riskier borrowers with access to credit based on the premise of controllable risks, such as through lending marketplaces, (online) micro-loan companies, or other types of FinTech credit intermediaries.

Table 10: Results of an Alternative Marketplace

I rerun baseline models on data from an alternative marketplace, YLD. Table 10 presents the results of regressions on ex-post measures of creditworthiness, *SuccessTimes*, *RepaidTimes*, and *Overdue*. All columns use OLS regressions. I control for the same set of application characteristics, borrower characteristics, and provincial environments as used in the regressions for RRD. Quarter dummies are also included. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. For variable definitions and details of their construction, see Appendix III.

	SuccessTimes			*RepaidTimes*			*Overdue*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
HHI	0.645***			1.047***			–7.585***		
	(0.163)			(0.137)			(0.285)		
CR3		0.392***			0.579***			–3.496***	
		(0.073)	0.342***		(0.063)			(0.139)	
CR6			(0.040)			0.443***			–5.341***
						(0.037)			(0.127)
Borrower Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provincial Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	117,910	117,910	117,910	117,910	117,910	117,910	117,910	117,910	117,910
R^2	0.0386	0.0387	0.0388	0.0831	0.0832	0.0831	0.0296	0.0285	0.0414
Adj. R^2	0.0385	0.0386	0.0386	0.0830	0.0831	0.0830	0.0295	0.0284	0.0413

4. Lending Marketplaces and Banks during a Crisis: The Case of COVID-19

4.1 Chapter Introduction

The COVID-19 pandemic causes severe disruptions to the world economy. Unlike the last crisis of 2007–2008 that started in the financial system, the pandemic hit the real economy first. The pandemic allows researchers to examine our financial system's ability to support the real economy. Does the performance of credit market components in providing liquidity to the real economy deviate from their usual performance during the pre-crisis period? In this chapter, I focus on how the pandemic alters the marketplace lending industry and challenges the banking sector in China. Specifically, how do lending marketplaces, a significant component of shadow banking, and commercial banks react to the pandemic? Do they stand ready to finance local individuals, households, and small businesses?

Despite the widespread outbreak in the first instance, China fast recovered from the shock through intensive government interventions and rigid lockdowns. Examining China's scenario allows concentrated observations on the performance of lending marketplaces and banks in such extreme situations where only online operations were plausible. This chapter may not only generate hints on the global pandemic impacts but also provide policymakers of other emerging economies with valuable references.

I develop hypotheses to visualise the impact of the pandemic on China's lending marketplaces. The government implemented consistent nationwide policies to control the pandemic effectively, such as regional lockdowns and mobility restrictions.[24] However, the policies dramatically decreased nationwide goods consumption. Business activities, including online business, were seriously disrupted. Such intervention is costly because it only stops business entities from getting income but does not stop them paying expenses. The

[24] http://english.www.gov.cn/news/topnews/202006/07/content_WS5edc559ac6d066592a449030.html

inaccessibility of business loans from banks during the pandemic worsened the business environment. I hypothesise that the pandemic overall decreased loan volumes of pre-existing marketplace borrowers, but the marketplace lending industry also attracted some newcomers from banks, which temporarily shut down their physical branches and thus could not serve some of their customers. I further hypothesise that large-sized loans originated during the pandemic are mainly contributed by these newcomers from banks.

To test my hypotheses, I must overcome two major difficulties. First, the loan-level bank data is inaccessible. Following the work of Tang (2019), I work around this problem by observing the changing pattern of loan-level marketplace data. Second, the pandemic's impact on the marketplace lending industry is a mixture of a direct impact on pre-existing marketplace borrowers and an indirect impact through marketplace newcomers from banks. Using carefully selected event windows, I successfully separate the direct and indirect impacts and respectively measure them.

The results of the baseline models support and go beyond my hypotheses. My main results are also found to be robust. Besides my hypotheses, I find that borrowers from banks typically contributed more long-term marketplace loans than pre-existing marketplace borrowers; on the contrary, pre-existing marketplace borrowers tended to borrow more small-sized and more short-term loans than the ex-ante level. The pandemic impacted cities unevenly. Wuhan and surrounding cities in Hubei faced a harder situation than other areas. I also find evidence that impacts on marketplace lending volume may be temporary, but whether impacts on marketplace loan size and loan maturity are also temporary is unclear.

Existing pandemic studies focus more on particular aspects of the real economy, such as the consumer and labour markets (see Baker et al., 2020; Bartik et al., 2020; Campello et al., 2020; Carlsson-Szlezak et al., 2020; Coibion et al., 2020 a, b; Dunn et al., 2020; Halling et al., 2020; Li, L. et al., 2020). Some studies explore the credit markets during the pandemic in the

United States and European countries (Halling et al., 2020; Li, L. et al., 2020). By comparison, the growingly important FinTech firms are relatively ignored by current literature, and how they are affected is largely unknown. Zachariadis et al. (2020) propose that the pandemic may have heterogeneous impacts on various FinTech firms in Europe. FinTech firms providing transactional services, especially those supporting cross-border transactions and international payments, are likely to suffer losses, whereas their credit-facilitating counterparts, such as lending marketplaces, may be uniquely positioned to grow. In short, there is a lack of study regarding the roles and behaviours of FinTech firms during the pandemic.

This chapter enriches the literature regarding the roles of FinTech institutions and credit market incumbents during a crisis. Current literature also gives relatively limited attention to reactions from China's markets, among which the stock market is studied the most. The reason could be that the stock market's reaction was immediate and raw data was readily available (Al-Awadhi et al., 2020; Huo and Qiu, 2020; Liu et al., 2020). However, China's stock market features speculative trading by retail investors and volatile regulations and has not effectively allocated resources to the real economy (Allen et al., 2009; Pan et al., 2016). The bond market in China is yet to mature and hence cannot provide sufficient financing support to the economy (Huang, 2006). Overall, China's stock and bond markets are still supplementary to its banking sector. The banking and shadow banking systems have remained indispensable to businesses and households in China in recent decades, especially during a crisis.

This chapter also contributes to the literature regarding the global relationship between bank credit and marketplace credit (Tang, 2019; De Roure et al., 2022). Although authorities of China have recently raised a campaign of "pushing the shadow banking into the light"[25], the roles of lending marketplaces during the pandemic remain unchanged. Allen et al. (2019)

[25] https://www.thebanker.com/Banking-Regulation-Risk/China-s-shadow-banking-sector-pushed-into-the-light

think that the marketplace lending industry may attempt to combine the intermediation advantages of bank financing and the information advantages of informal financing. My proprietary dataset from the marketplace lending industry may facilitate the study of informal financing, which is typically difficult to analyse because of data scarcity, and its interaction with the banking industry. Moreover, my research may shed light on the role of marketplace lending and informal financing in supporting local economies during the pandemic in other emerging markets of Asia.

The rest of the chapter is structured as follows. Section 4.2 provides a background of China's credit market policy and credit market status. This section also includes a brief chapter literature review, which motivates the propositions I study in the chapter. Data sources and variable construction are explained in Section 4.3. Baseline models and measurement techniques are also explained in this section. Measurement results are presented and discussed in Section 4.4. Robustness checks are conducted in Section 4.5, and Section 4.6 concludes the chapter.

4.2 Background and Hypotheses Development

4.2.1 Lockdown, Nationwide Mobility Restrictions and Recovery from the Pandemic

China is the first country where the government controlled the pandemic by using regional lockdowns and restrictions on population mobility. These policies were first used in Wuhan on 23 January 2020. Lockdowns were then extended to other cities in Hubei (Lau et al., 2020), followed by lockdowns of almost one-third of the cities across the country (He et al., 2020). Another widely implemented measure was restrictions on community-level mobility of the population. Wuhan fully implemented 24-hour mobility restrictions. Except for medical treatment and epidemic control activities, entry into and exits from communities were prohibited. In other areas, mobility restrictions were generally implemented in urban communities and rural villages; only one household member was allowed to go outside to

buy necessities of life for limited times. Express delivery and takeaway services were generally prohibited. In extreme cases, such as when confirmed cases of infection were found, entries and exits were prohibited at all times.

These intervention policies were proven effective (Hsiang et al., 2020; Lau et al., 2020). As shown in Figure 4, daily new confirmed cases sharply decreased after the initial outbreak. However, there were also costs. Most physical stores that provide non-essential goods and services were not allowed to open. Online store businesses were also halted because logistics became unrealistic when intercity transportation shut down and mobility restrictions continued. Unprecedented declines in goods supply led to a dramatic drop in nationwide goods consumption (Chen, H. et al., 2021). I expect a simultaneous drop in short-term consumer loans across the country, as demonstrated in Figure 5. Since no evidence shows that a platform's pre-existing borrowers [26] differed from others in their consumption behaviour or business strategy, theoretically, these borrowers should also reduce demand for short-term loans within the corresponding period. According to Appendix IV.1, short-term loans are always the dominating type on RRD regardless of the pandemic, so I expect loans from pre-existing marketplace borrowers to decline during the pandemic. Thus, my first hypothesis is:

Hypothesis 1: The pandemic directly inhibited the borrowing volume of pre-existing marketplace borrowers.

[26] Pre-existing marketplace borrowers here are a generalised definition, which includes actual borrowers who have already borrowed from marketplaces and potential borrowers who share key features with actual borrowers and potentially borrow from marketplaces in the future, even if COVID-19 had not occurred.

Figure 4: Daily New Confirmed Cases of China during the First Six Months of 2020

This figure shows the outbreak and recovery of the pandemic in China. Data is collected from Chinese Centre for Disease Control and Prevention (CDC). On 12 February 2020, 15152 new confirmed cases were reported (a total of 13,332 clinically diagnosed cases in Hubei were counted into new confirmed cases all at once that day).

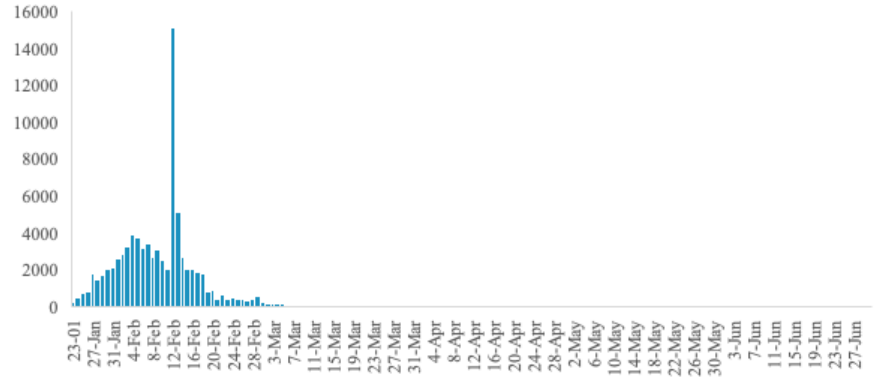
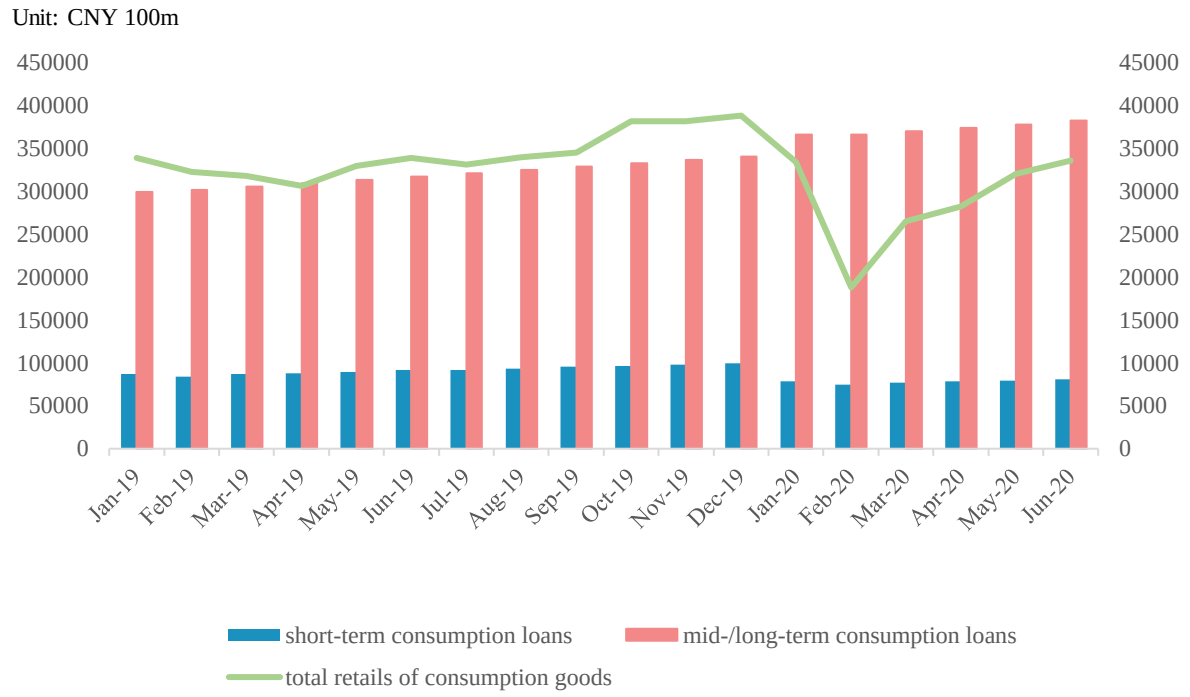


Figure 5: Trend of Total Retails of Consumption Goods and Consumption Loans in China's Society

This figure shows the monthly trends of three variables: 1) nationwide existing volume of short-term consumption loans (blue bars), 2) nationwide existing volume of mid-/long-term consumption loans (pink bars) and total nationwide consumption of goods (green line). Information about consumption loans is collected from PBC, and they define short-term loans as loans with maturities of less than one year. Data about the total consumption of goods in China's society is collected from CEInet Statistics Database. The right (left) vertical axis measures the magnitude of short-term consumption loans and total retail of consumption goods (mid-/long-term consumption loans). As shown, the consumption of goods starts to decline in January 2020 and even further decreases during February. This trend reverses during the following months. In February 2020, short-term consumption loans also mildly decrease and recover during the following months. By contrast, mild- and long-term consumption loans increase during February and the following months.



4.2.2 Worse Access of Small Businesses to Bank Credit during the Pandemic

The allocation of credit from China's banks to state-owned enterprises (SOEs) and SMEs has always been unbalanced. Besides commercial judgements, China's banks also value political connection, state ownership and accompanying implicit guarantee (Firth et al., 2009). This disproportionate credit allocation was further enhanced after the economic stimulus during the global financial crisis (Liu et al., 2018; Cong et al., 2019). Small businesses in China had even less access to bank credit during the pandemic, but due to a different reason. That reason is the pandemic's interruption of bank lending procedures. Unlike the digitalised

origination procedure of consumer loans in China, the origination of commercial loans requires much more on-site application and field inspections. As stated in the document "Interim Measures for the Administration of Working Capital Loans" issued by the China Banking Regulatory Commission (CBRC):

> *"… When reviewing the borrower's loan application, the lender shall perform due diligence in the form of a combination of on-site and off-site, form a written report, and be responsible for the authenticity, completeness and effectiveness of its content. …"* [27]

China's banks also publish similar requirements on their websites. For example, the Bank of China (BoC) regulates in its document "Credit Process and Management" that a hard copy of application materials is required to be submitted to the nearest branch; if a business applicant passes the initial screening, a manager will contact the applicant and visit the business for a follow-up investigation.[28]

The pandemic and accompanied mobility restrictions had made such procedures impractical. As a result, enterprises generally faced stringent access to bank credit during the restrictions. Small businesses were likelier to switch to a platform because they typically do not have or only have limited credit lines (Ma et al., 2019). Therefore, my next hypothesis is:

Hypothesis 2a: Some borrowers from banks transferred to lending marketplaces. Thus, the pandemic also indirectly increased marketplace lending volume through banks.

Hypothesis 1 and *2a* imply that the pandemic's comprehensive impact on marketplace lending volume combined two effects. First, the pandemic directly impacted pre-existing marketplace borrowers. Second, the pandemic also indirectly impacted the marketplace

[27] https://www.cbirc.gov.cn/cn/view/pages/ItemDetail.html?docId=3139&itemId=928&generaltype=0
[28] https://www.bankofchina.com/cbservice/cb8/201309/t20130917_2510271.html

lending industry through marketplace newcomers from banks. Considering the dominant position of banks in providing credit, I further hypothesise that:

*Hypothesis 2b**:** Due to the enormous volume of China's banking industry, even if a small portion of the bank borrowers transferred to lending marketplaces, it could reverse the direct impact of the pandemic on marketplace lending volume and, thus, the overall impact on marketplace lending volume was positive.*

4.2.3 Different Profiles of Borrowers from Banks and Lending Marketplaces

Literature regarding profiles of marketplace borrowers and bank-dependent borrowers focuses more on the United States and Europe markets. De Roure (2016) finds that the average loan size in a German platform, Auxmoney, is smaller than most loans originated by German banks. Tang (2019) finds that borrowers squeezed out by banks tend to borrow larger loans than pre-existing marketplace borrowers. China's bank-dependent borrowers may also have different profiles from marketplace borrowers. Specifically, I hypothesise that:

Hypothesis 3: Borrowers from banks tended to borrow more large-sized loans than pre-existing marketplace borrowers during the pandemic.

However, the above hypotheses do not constitute the whole story. Besides these hypotheses derived from policies, documents, and literature, I also find other interesting results after the measurements.

4.3 Data and Methodology

4.3.1 Data from the Database of NIFA

The National Internet Finance Association of China (NIFA) was a self-regulation institution established and organised by the government of China, which provided and updated authoritative information about China's internet finance.[29] By 31/01/2020, there

[29] https://www.chinabankingnews.com/wiki/national-internet-finance-association-china-中国互联网金融协会/

were 78 lending marketplaces in NIFA's database. Appendix IV.2 presents the summary statistics of these platforms. These data are used to recognise qualified research identities. NIFA also provides 29 variables for most loans from these 78 platforms.[30] I collect these platform-level and loan-level data with techniques shown in Appendix II.1 and Appendix II.2. These data are an informational complement to data collected from the commercial website of RRD.

4.3.2 Data from the Commercial Website of lending marketplace RRD

I choose RRD for three reasons: first, based on data from NIFA, its business size is bigger than the average. By 31 January 2020, its cumulative borrowing amount had reached CNY 101,465,580,000, almost twice the average; it had successfully brokered 4,718,523 loans since its establishment; 2,838,793 borrowers and 1,081,989 lenders had successfully borrowed or lent money through RRD. This sample from RRD is large and representative to support further measurements. Second, RRD has a high level of information transparency and provides 37 variables to profile most projects.[31] Another reason is that loan information on RRD is open-source, and data availability is ideal. I have collected 8,034,610 loan records[32] from RRD's commercial website and NIFA from 11 October 2010 to 30 June 2020. I merge the data and extract 81 effective variables for every observation. Appendix IV.3 contains the summary statistics for some key variables. Appendix VI depicts long-term trends of the number, the amount, the average size, and the average maturity of new loans.

4.3.3 Methodology

4.3.3.1 Justification of Panel-data Regression Model Settings

My proposed hypotheses require observing the pandemic's heterogeneous impacts on different cities over time, so I cluster my loan-level data by cities and by quarters and

[30] Details of names and descriptions of these 29 variables are not presented here. However, this information is available from the authors upon reasonable request.

[31] Details of names and descriptions of these 37 variables are not presented here. However, this information is available from the authors upon reasonable request.

[32] Both successful and some unsuccessful applications are included.

calculate the necessary attributes of loans from various cities during different quarters. Then it is natural to adopt a panel-data regression model to analyse these attributes. The selected study period is from the first quarter of 2011 (2011Q1) to the second quarter of 2020 (2020Q2).[33] Focusing on the long-term trend instead of quarters around the pandemic avoids the model's overfitting to the nearest period.

These necessary attributes include the loan volume, average loan size, quantiles in the loan size distribution, average loan maturities, and quantiles in the loan maturity distribution of every city during every quarter, which become dependent variables.

I use dummy variables to indicate the outbreak and stages of the pandemic. Many recent studies also choose this strategy. However, it is necessary to distinguish the different ways they set these dummy variables. A commonly used method is using a dummy variable to indicate whether the pandemic has occurred (no further differentiation of the pandemic's sub-periods) (Albuquerque et al., 2020; Campello et al., 2020; Dunn et al., 2020; Li et al., 2020). Another method adopts dummy variables to represent the standard sub-periods (daily, weekly, monthly, or quarterly) during the event (Demir & Javorcik, 2020; McLaren, 2021). The second method reveals not only the pandemic's aggregate influence but also its dynamics. Method 3 adopts dummy variables to indicate tailored sub-periods or waves of surveys and can depict the event boundary more precisely (Baker et al., Forthcoming; Cheng et al., 2020; Falato et al., 2021; Galasso et al., 2020; Gupta et al., 2020). Since my study is not based on surveys and there are no clear boundaries between the pandemic's stages in China, I choose method 2 to set dummy variables. Furthermore, to reveal heterogeneous impacts of the pandemic on cities with different pandemic severity, I interact the dummies indicating the pandemic with the dummies indicating certain cities.

[33] I use this abbreviation system to describe a particular quarter of a particular year more briefly.

I adopt a set of city-specific control variables to prevent city-specific factors from interfering with my measurement results. Other unknown city-specific factors are controlled by city fixed effects. I treat my first measurement model as a fixed-effect model, as argued by Green and Tukey (1960) and Searle et al. (2009) that, if the studied sample exhausts the population, it should be considered a fixed-effect model. Since my sample includes all cities in China, city-specific effects should be considered fixed effects.

Another factor that should be controlled is seasonality. My first measurement model is a long-term quarterly-basis model, which is likely to be subject to the seasonality effect. So I adopt three dummy variables indicating the first quarter, the second quarter, and the third quarter of a year, respectively.

To control for level shifts in some trends shown in Appendix VI, I use optional dummy variables to indicate whether a major level shift has occurred. Details about how I set these dummy variables are reported in Appendix VI.

I do not further apply quarter fixed effects as they may cause severe multicollinearity. Instead, I use year fixed effects to work around this problem. After justifying the model choice and variable settings, I give my first measurement model below:

$$y_{c,t} = \alpha_c + \sigma_y + \beta_1 Pandemic1_{c,t} + \beta_2 Pandemic2_{c,t} + \beta_3 (City * Pandemic)_{c,t} + \gamma_1 Controls_{c,t} + \gamma_2 Seasonality_t + \gamma_3 LevelShift_t + \varepsilon_{c,t} \quad (7)$$

where *c* denotes prefecture-level cities and *t* indexes quarters. *y* is the set of relevant dependent variables with details summarised in Appendix V, Panel 1. α is the city fixed effects. σ is the year fixed effects. *Pandemic1* and *Pandemic2* are two dummy variables indicating 2020Q1 and 2020Q2 and are used to account for the pandemic's impacts and dynamics. Hereafter, *Pandemic1* and *Pandemic2* are called "pandemic dummies". *City* * *Pandemic* is a set of interaction terms between city dummies and pandemic dummies and is designed to reveal the pandemic's heterogeneous impacts among different cities during

2020Q1 & Q2. I examine these two quarters separately to reflect the dynamic influence of the pandemic. *City* is a set of city dummy variables with details shown in Appendix V, Panel 2. *Controls* is the set of city-level control variables[34]; their details are shown in Appendix V, Panel 3. *Seasonality* is the set of three quarter dummies indicating whether the current quarter is the first, the second, or the third quarter of a year. Hereafter, dummy variables in $Seasonality_t$ are referred to as "quarter dummies". *LevelShift* is an optional dummy variable indicating whether a certain level shift occurred in a trend.[35] Details of quarter dummies and *LevelShift* are listed in Panel 4 of Appendix V. ε is an error term.

Model (7) aims to measure the comprehensive impact of the pandemic on lending marketplaces. However, since the pandemic is a comprehensive shock impacting both the marketplace lending industry and the banking industry, and the impact on the banking industry can be further passed to the marketplace lending industry through marketplace newcomers, Model (7) fails to separate these mixed effects. So, I need other models to separate these effects. Next, I design another measurement model using daily-basis data and a DID approach. The DID regression model extracts the pandemic's direct impact on a platform before the platform accepted newcomers from banks and these mixed effects coexisted.

4.3.3.2 Justification of DID Measurement Model Settings

I develop a DID model to measure the pandemic's direct impact on pre-existing marketplace borrowers. There exists a period when the pandemic was mainly located in Wuhan and mildly spread in some adjacent cities in Hubei. During that period, its impact on

[34] Loan information is gathered quarterly; however, city-level control variables are only available yearly. As a result, for a record that profiles the situation of marketplace loans of a specific city in a particular quarter, I append values of control variables of that city collected at the end of the previous year. For example, if a record depicts Beijing's marketplace loan condition in 2019Q3, I append the control variable data collected at the end of 2018 to that record.

[35] This variable's optionality means it is not necessarily included in every regression model. Details about the setting of this term and why it is optional are fully explained in Appendix VI.

the banking industry could not be passed to the marketplace lending industry because physical branches of banks still opened and could serve bank-dependent borrowers as usual. Therefore, I extract the pandemic's direct impact on platforms by comparing the ex-ante and ex-post situations of affected and unaffected areas using the DID approach.

Concretely, to extract the pandemic's direct impact on pre-existing marketplace borrowers, I carefully pick an event window from 01 December 2019 to 22 January 2020 for my DID model. Days before 27 December 2019 are the control period as the virus was identified in Wuhan for the first time on 27 December 2019. However, the danger of the virus was seriously underestimated at that time. On 10 January 2020, test kits for coronavirus were invented, and governments started publishing numbers of pandemic cases. The public also started to take the threat of this new virus seriously. On 23 January 2020, Wuhan announced lockdown and mobility restrictions with nationwide cities then following these policies. Most business activities and bank branches shut down during these physical restrictions. The pandemic's indirect impact through the shutdowns of banks began. However, this indirect impact needs to be filtered out in this model, so I end the event window one day before the launch of such physical restrictions, that is, 22 January 2020. Then, any patterns revealed within the event window can be treated as the pandemic's direct impact on pre-existing marketplace borrowers.

I set two treat-post interaction terms following a typical manner of the DID approach. Specifically, I set one city dummy to indicate whether the city is the treated city, Wuhan. Data from other cities in Hubei are excluded as most cases are concentrated in Wuhan, while the other cities only suffered moderate severity. This strategy allows me to compare Wuhan and cities outside Hubei during the event window and make the comparison most significant. Then, I let this city dummy interact with two event dummies. The first event dummy indicates whether the virus has been identified. Its interaction term with the city dummy controls for the effect of virus identification. The second event dummy indicates whether the

governments have started publishing numbers of pandemic cases. Its interaction term with the city dummy reflects the direct impact of the pandemic on the marketplace lending industry.

Since my sample still encompasses most cities in China, I still treat city-specific effects as fixed effects. These city fixed effects are included in the DID measurement model. To make the measurement results more concrete, I also control for several kinds of cyclicality by employing day-specific dummies.

After justifying the model settings, I provide my DID measurement model:

$$y_{c,t} = \alpha_c + \beta_1 Treat_c * Post1_t + \beta_2 Treat_c * Post2_t + \gamma Cyclicality_t + \varepsilon_{c,t} \quad (8)$$

where c denotes prefecture-level cities and t indexes quarters. y is the set of interested dependent variables with details summarised in Appendix V, Panel 1. α is city fixed effects. *Treat* is a dummy variable equal to 1 if the city is Wuhan and equal to 0 if the city is outside Hubei. *Post1* equals 1 for the period after the virus was identified for the first time. *Post2* equals 1 for the period after test kits were invented and governments started publishing the pandemic cases. *Cyclicality* is a group of day-specific dummies designed to hold year fixed effects, quarter fixed effects, within-month cyclicality, within-week cyclicality and spring festival fixed effects.

Theoretically, Model (8) should reveal the direction of the pandemic's direct impact on pre-existing marketplace borrowers. By combining the results of Model (7) and Model (8), I can also infer the direction of the pandemic's indirect impact on a P2P platform through the banking sector. Such inferences will be further examined in the robustness test section.

Both Model (7) and Model (8) assume that the pandemic's time attribute is a qualified proxy variable of its impact. However, this assumption can be problematic, especially when the reality is too noisy, and the time dummies may include the influence of the pandemic and

incorporate other unrelated factors. I partially release this assumption in the robustness test section by employing an alternative proxy variable.

4.4 Measurement Strategies, Measurement Results, and Explanations

I aim to discuss the impacts of the pandemic on a P2P platform from three dimensions: the loan volume, the loan size, and the loan maturity. I will apply my models in these three dimensions. Although the interest rate is also an essential attribute for loans, in my case, it is not priced by the market nor the interaction between credit supply and credit demand. Instead, the interest rate is set by the platform based on the characteristics of a borrower before the online bid of a loan project (Jiang et al., 2021). This mechanism partially explains why P2P loan rates are overall insensitive to the pandemic; thus, I do not discuss the loan rate dimension.

4.4.1 The Loan Volume

To test *Hypotheses 1*, *2a*, and *2b*, I run Model (7) and Model (8) using marketplace lending volume as their left-hand-side variable. I adopt two measures: the total amount of funded loans and the number of funded loans. To remove the undesired influence of city size, I normalise all the dependent variables by city population (in ten thousands). I further take the natural log of the dependent variables to enhance the explanatory power of my models.

Table 11 lists the measurement results when I run Model (7) and Model (8) over loan numbers and cumulative loan amounts. Based on the results reported under Panel 1, I can find that after controlling for *Seasonality*, the comprehensive impacts of the pandemic on both loan numbers and cumulative loan amounts are still significantly positive. However, this positive influence diminished during the second quarter as the pandemic became relatively controlled. It implies that the pandemic's comprehensive impact on marketplace lending volume may be temporary nationwide instead of permanent. Panel 2 lists the results of Model (8). It shows that the pandemic’s direct impact on cumulative loan amounts was significantly

negative, while the pandemic's direct impact on loan numbers was insignificantly negative; the pandemic overall suppressed the borrowing activities of pre-existing marketplace customers, which supports *Hypothesis 1*.

Banks have always been the dominating financing channel in China, and the shutdown of their physical branches beyond the Spring Festival holiday was the major financial shock during 2020Q1 and 2020Q2. So, I can arguably infer that after filtering out the direct impact on pre-existing marketplace customers, the rest of the pandemic's influence was likely attributed to the banking sector. It means that the lockdowns and mobility restrictions made China's banks unable to serve some bank-dependent borrowers; at least some of these unserved bank-dependent borrowers switched to marketplaces and reversed the pandemic's comprehensive impact on marketplace loan volume from negative to positive. Thus, the results arguably support *H2a* and *H2b*. The diminution of coefficients of *Pandemic1* to *Pandemic2* also adds extra evidence for these hypotheses because physical bank branches resumed opening during 2020Q2. In the robustness test section, these hypotheses are further examined.

Panel 1 also shows the uneven impacts of the pandemic on different cities during 2020Q1 and 2020Q2. Wuhan's P2P borrowing activities shrank heavily, and this trend intensified further during the ongoing pandemic. I can observe a similar situation in other Hubei cities. The pandemic suppressed the marketplace borrowing activities in these cities. The effect was statistically insignificant during 2020Q1 but became significant during the next quarter. As indicated earlier, the pandemic's influence might be a mixture of two effects, which may partially explain the situation in Hubei. The first possible explanation is that the pandemic in Hubei, especially Wuhan, was severe, and borrowing activities from pre-existing marketplace borrowers shrank heavily; the contribution of newcomers to the marketplace could not fully offset the initial negative effect. Another possible reason is that governments at various levels had provided extra financial support for citizens and enterprises in Hubei. For example, from

February to June, enterprises of all sizes in Hubei could be exempted from endowment insurance, unemployment insurance, and industrial injury insurance. Meanwhile, enterprises could apply to delay the payment of housing provident funds, and no overdue treatment would be made if employees failed to repay housing provident loans regularly due to the pandemic.[36] Governments provided the option of deferred tax payments for SMEs in Hubei. Besides, Value-added Tax (VAT) could be exempted for small taxpayers in Hubei.[37] PBC also provided more credit to support SMEs by unblocking extensions, renewing loans, and lowering lending rates. By 1 February, the ministry of finance (the provincial department of finance) had allocated 900 million yuan (240 million yuan) in transfer payments for Wuhan.[38] Human costs, taxes, and interests could be a huge burden for SMEs during the lockdowns. Such large-scale comprehensive financial support might demotivate people in Hubei to borrow from platforms.

By contrast, the situation of cities in the capital circle was not significantly different from other non-Hubei areas, although very rigorous restrictions were also implemented inside the capital circle. It implies that the pandemic's local severity is likelier to suppress marketplace borrowing activities than the rigorousness of controls.

[36] Information about the government's financial support for corporate employee insurance was obtained from KPMG. https://home.kpmg/xx/en/home/insights/2020/04/china-government-and-institution-measures-in-response-to-covid.html

[37] Information about the government's tax relief for SMEs was obtained from KPMG. https://home.kpmg/xx/en/home/insights/2020/04/china-tax-developments-in-response-to-covid-19.html

[38] Information about transfer payments was obtained from *China Financial and Economic News*. http://www.cfen.com.cn/zyxw/jj/zhaunti_126/202002/t20200213_3469365.html

Table 11: Impacts of the Pandemic on Funded Marketplace Loan Volume

Panel 1	Amount	Number	*Panel 2*	Amount	Number
	(1)	(2)		(3)	(4)
pandemic1	0.682***	0.520***	Treat * Post1	0.094	0.105
	(5.63)	(5.75)		(0.75)	(1.38)
pandemic2	0.213*	0.216**	Treat * Post2	-0.365**	-0.099
	(1.69)	(2.32)		(-2.52)	(-1.12)
Wuhan * pandemic1	-2.480*	-1.806*			
	(-1.69)	(-1.72)			
Wuhan * pandemic2	-3.124**	-2.355**			
	(-2.13)	(-2.24)			
Hubei * pandemic1	-0.487	-0.444			
	(-1.08)	(-1.37)			
Hubei * pandemic2	-0.875*	-0.931***			
	(-1.94)	(-2.87)			
CapitalCircle * pandemic1	0.122	0.048			
	(0.28)	(0.15)			
CapitalCircle * pandemic2	0.093	0.061			
	(0.21)	(0.20)	Within-month Cyclicality	Y	Y
LevelShift	N	Y	Within-week Cyclicality	Y	Y
Seasonality	Y	Y	Spring Festival FE	Y	Y
Controls	Y	Y	Quarter FE	Y	Y
Year FE	Y	Y	Year FE	Y	Y
City FE	Y	Y	City FE	Y	Y
Observations	7,994	7,994	Observations	14,950	14,950
R^2	0.7383	0.8554	R^2	0.8217	0.8861

This table reports the pandemic's impacts on funded P2P loan volume of a city. Funded volume is measured either by the total amount requested in successful loan applications per 10,000 residents (Column (1) & (3)) or by the total number of funded loan per 10,000 residents (Column (2) & (4)) in a given city. I further take a natural-log transformation for the dependent variable to enhance the explaining power of the model.

Panel 1 reports the pandemic's comprehensive impact on the funded P2P loan volume of cities in China as estimated by Model (7), which uses city-quarter data during the period 2011-2020. pandemic1 and pandemic2 are the pandemic dummies and indicate the stages of the pandemic. Quarter fixed effects (FE) are not included to avoid multicollinearity. Instead, year fixed effects and city fixed effects are included in all regressions. Coefficients of control variables, *Seasonality*, *LevelShift*, year and city fixed effects are not presented here, but can be offered on request. Distributions and standard errors are clustered at the city-quarter level, and t-statistics are given in parentheses.

Panel 2 reports the pandemic's direct impact on the funded P2P loan volume of cities in China as estimated by Model (8), which uses city-day data from 01 December 2019 to 22 January 2020. $Treat_c * Post1_t$ and $Treat_c * Post2_t$ are two interaction terms used to compare Wuhan and cities outside Hubei before and after certain moments, where $Post1_t$ indicates the moment coronavirus is first found, and $Post2_t$ indicates the moment the government starts publishing the pandemic dynamics. Year fixed effect, quarter fixed effects, within-month cyclicality, within-week cyclicality and spring festival fixed effects are included in all regressions. Distributions and standard errors are clustered at the city-day level, and t-statistics are given in parentheses. *p<0.10, **p

4.4.2 The Loan Size

This section will first focus on the pandemic's impact on the average loan size. However, the pandemic might cause idiosyncratic effects on borrowers with different borrowing sizes. These effects may be neutralised or covered if I only study the average loan size. I then analyse how the pandemic influences the distribution of loan sizes. I first cluster and construct distributions by cities and quarters. Next, I slice these distributions from selected percentiles, treat values of every selected percentile as a dependent variable, and run my models separately.

As shown in Table 12, Panel 1, the average loan size significantly increased during 2020Q1, and this trend reversed to an insignificant extent during the second quarter. Another pattern is that taking the 55th and 65th percentile (column [6] and column [7]) as the centre, the coefficients of pandemic1 on the left (right) side tend to be significantly negative (positive). A negative/left (positive/right) movement of the *k*th percentile means more post-shock originated loans have sizes smaller (bigger) than the *k*th percentile of the pre-shock loan size distribution. Thus, the results mean that both the left and right tail of loan size distribution became thicker after the pandemic. Unlike the pandemic's impact on the loan volume, the distribution of loan sizes did not experience a reverse during 2020Q2 as indicated by the coefficients of *pandemic2*. Instead, the 75th and 85th go even further to the right. My data do not provide significant evidence that the pandemic's impacts on the average loan size and the distribution of loan sizes are temporary. Insignificant coefficients of interaction terms in Panel 1 illustrate that the pandemic did not add any influence on the loan size distribution of Wuhan, other Hubei cities or cities in the capital circle.

Panel 2 of Table 12 describes the pandemic's direct impact on pre-existing marketplace borrowers. It shows that once the governments started publishing the numbers of pandemic cases, the average size of loans borrowed by pre-existing marketplace borrowers dramatically decreased. However, only the 95th percentile decreases significantly, which means new loans

by pre-existing borrowers mainly fell into the left side of the 95 percentile of the original distribution. It implies that pre-existing borrowers tended to borrow more small-sized loans than before the pandemic, and this preference changed the ex-ante loan size distribution. Based on the same logic as analysing the pandemic's impacts on the loan volume, I arguably infer that after filtering out the pandemic's direct impact on pre-existing borrowers, the rest of the comprehensive impact was attributed to banks shutting down. I can also arguably conclude that some marketplace newcomers from banks borrowed more on average than pre-existing marketplace borrowers and made the right tail of loan size distribution move further to the right. *Hypothesis 3* is arguably supported. The conclusion will be further examined in the robustness test section.

Table 12: Impacts of the Pandemic on Funded Marketplace Loan Sizes – Percentiles and Average

	5th	15th	25th	35th	45th	55th	65th	75th	85th	95th	Average
	(1)	(2)	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]
Panel 1 The pandemic's comprehensive impact on the loan size											
pandemic1	0.015	-0.097	-0.164***	-0.204***	-0.175***	-0.085	0.046	0.126**	0.139**	0.325***	0.106*
	(0.24)	(-1.59)	(-2.68)	(-3.30)	(-2.81)	(-1.35)	(0.72)	(1.96)	(2.12)	(4.75)	(1.84)
pandemic2	0.306***	0.024	0.000	0.010	-0.102	-0.075	0.041	0.165**	0.212***	0.007	-0.051
	(4.96)	(0.38)	(0.00)	(0.15)	(-1.58)	(-1.16)	(0.63)	(2.50)	(3.15)	(0.10)	(-0.87)
Wuhan * pandemic1	-0.714	-0.902	-0.900	-1.042	-1.07	-1.182	-1.103	-1.068	-0.864	-0.787	-0.631
	(-0.98)	(-1.21)	(-1.21)	(-1.39)	(-1.41)	(-1.55)	(-1.43)	(-1.37)	(-1.09)	(-0.95)	(-0.90)
Wuhan * pandemic2	-0.714	-0.877	-0.981	-0.934	-1.161	-1.100	-1.257	-1.176	-0.895	-0.661	-0.825
	(-0.98)	(-1.18)	(-1.32)	(-1.25)	(-1.53)	(-1.44)	(-1.63)	(-1.51)	(-1.13)	(-0.80)	(-1.18)
Hubei * pandemic1	-0.058	0.055	0.061	0.063	0.195	0.065	0.053	0.046	-0.040	-0.059	-0.043
	(-0.27)	(0.25)	(0.28)	(0.28)	(0.87)	(0.29)	(0.23)	(0.20)	(-0.17)	(-0.24)	(-0.21)
Hubei * pandemic2	-0.048	0.145	0.182	0.070	0.364	0.219	0.264	0.189	0.063	-0.052	0.056
	(-0.22)	(0.66)	(0.83)	(0.32)	(1.62)	(0.97)	(1.16)	(0.82)	(0.27)	(-0.21)	(0.27)
CapitalCircle * pandemic1	0.063	0.019	-0.022	-0.021	-0.041	0.029	0.065	0.120	0.016	0.034	0.072
	(0.30)	(0.08)	(-0.11)	(-0.10)	(-0.19)	(0.13)	(0.30)	(0.54)	(0.07)	(0.14)	(0.36)
CapitalCircle * pandemic2	0.074	0.019	-0.009	-0.011	-0.062	-0.016	-0.027	0.049	-0.005	-0.017	0.030
	(0.35)	(0.09)	(-0.04)	(-0.05)	(-0.29)	(-0.07)	(-0.12)	(0.22)	(-0.02)	(-0.07)	(0.15)
LevelShift	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Seasonality	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	7994	7994	7994	7994	7994	7994	7994	7994	7994	7994	7994
R^2	0.737	0.730	0.717	0.711	0.704	0.692	0.679	0.667	0.657	0.616	0.691

Panel 2 The pandemic's direct impact on the loan size

Treat * Post1	-33.306	-10.834	-17.435	-39.864	-8.406	-79.888	-29.407	-108.789	-459.901	9748.054***	196.629
	(-0.43)	(-0.12)	(-0.17)	(-0.29)	(-0.05)	(-0.38)	(-0.11)	(-0.26)	(-0.43)	(2.82)	(0.43)
Treat * Post2	13.820	-11.092	6.082	-55.593	53.722	50.073	-18.975	51.432	-45.355	-33082.2***	-2305.1***
	(0.15)	(-0.11)	(0.05)	(-0.35)	(0.28)	(0.20)	(-0.06)	(0.11)	(-0.04)	(-8.24)	(-4.39)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Within-month Cyclicality	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Within-week Cyclicality	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Spring FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	15022	15022	15022	15022	15022	15022	15022	15022	15022	15022	15022
R2	0.419	0.315	0.251	0.203	0.213	0.219	0.186	0.129	0.202	0.454	0.524

Panel 1 reports the pandemic's comprehensive impact on the quantiles in loan size distribution and the average loan size as estimated by Model (7), which uses city-quarter data for the period 2011-2020. In each of Columns [1] - [10], the dependent variable is the natural log of *k*th percentile ($k \in \{5, 15... 95\}$) of the loan size distribution; in Column [11], the dependent variable is the natural log of average loan size. All columns include the same set of controls as in Appendix V, Panel 3, the same setting of *LevelShift* as described in Appendix VI, and include *Seasonality*, year and city fixed effects. Coefficients of control variables, *Seasonality*, *LevelShift*, year and city fixed effects are not presented here, but can be offered on request. Distributions and standard errors are clustered at the city-quarter level, and t-statistics are given in parentheses.
Panel 2 reports the pandemic's direct impact on the loan size distribution as estimated Model (8), which uses city-day data from 01 December 2019 to 22 January 2020. In each of Columns [1] - [10], the dependent variable is the *k*th percentile ($k \in \{5, 15... 95\}$) of the loan size distribution; in Column [11], the dependent variable is the average loan size. All columns include the same set of explanatory variables. Year fixed effect, quarter fixed effects, within-month cyclicality, within-week cyclicality and the spring festival fixed effects are controlled. Coefficients of these fixed effects are not presented here but can be offered on request. Distributions and standard errors are clustered at the city-day level, and t-statistics are given in parentheses.
*p<0.10, **p<0.05, ***p<0.01

4.4.3 The Loan Maturity

RRD only provides several loan maturity options, making the distribution of loan maturities highly discrete. Thus, I use regressions on percentiles as well as regressions on frequencies of maturity-specific loans to study the pandemic's impacts on loan maturity.

As shown in Panel 1 of Table 13, the average maturity size significantly increased during 2020Q1, and this trend was further enhanced significantly during the second quarter. Another pattern is that taking the 25th and 35th percentile regression results (column [3] and column [4]) as the centre, the coefficients of *pandemic1* on the left (right) side tend to be significantly negative (positive). This pattern is because only 3-month and long-term loans significantly increased during the first quarter, where the results are listed in Panel 1 of Table 14. The distribution of loan maturity does not experience a reverse during the second quarter according to the coefficients of *pandemic2*. Instead, it is further enhanced in total. This enhanced trend is also reflected in Panel 1 of Table 14.

The coefficients of *pandemic1* and *pandemic2* in Table 13 and Table 14 also indicate an ongoing nationwide trend of the pandemic's comprehensive impact on the average loan maturity and the loan maturity distribution, so my data do not provide significant evidence that the comprehensive impact of the pandemic is temporary just based on the data of the first two quarters of 2020.

Panel 1 of Table 13 also shows the pandemic's additional impacts on Wuhan. As shown, the 15th to 45th percentiles significantly move left, which means the pandemic had altered the ex-ante distribution of loan maturities. This pattern is also reflected by the results in Panel 1 of Table 14. During 2020Q1, 12-month loans and 36-month loans funded in Wuhan significantly dropped. During 2020Q2, 36-month loans funded in Wuhan significantly dropped again. The fact that 3-month, 6-month, and 9-month loans only decreased by an insignificant degree implies that, although the pandemic heavily hit the marketplace lending

volumes in Wuhan, short-term loans had not heavily shrunk as these loans might be more suitable for short-term turnover. Although Panel 1 of Table 14 also shows some drops in funded loans with various maturities in other cities in Hubei and cities in the capital circle, such drops tended to be proportional and thus did not alter the ex-ante distribution of loan maturities shown in Panel 1 of Table 13.

Panel 2 of Table 13 shows the pandemic's direct impact on the loan maturity distribution of pre-existing marketplace customers. It shows that once the governments started publishing the pandemic cases, the average maturity of loans borrowed by pre-existing marketplace borrowers dramatically decreased. However, only the 95th percentile decreases significantly, which means most pre-existing marketplace borrowers' new loans were smaller than the 95th percentile of the ex-ante distribution of loan maturities. Panel 2 of Table 14 complements Panel 2 of Table 13 by showing that only 3-moth, 6-month, and 12-month loans experience significant increases after publishing the pandemic's dynamics. It implies that pre-existing marketplace borrowers tended to borrow more short-term loans than before the pandemic. This behaviour changed the ex-ante loan maturity distribution. Based on the same logic as before, I can arguably infer that long-term loans were most likely borrowed by marketplace newcomers from banks.

Table 13: Impacts of the Pandemic on the Funded Marketplace Loan Maturity – Percentiles and Average

	5th [1]	15th [2]	25th [3]	35th [4]	45th [5]	55th [6]	65th [7]	75th [8]	85th [9]	95th [10]	Average [11]
Panel 1 The pandemic's comprehensive impact on the loan maturity											
pandemic1	0.1667 (0.34)	-1.792*** (-3.07)	-0.080 (-0.13)	0.829 (1.31)	1.340** (2.07)	1.619** (2.5)	1.704*** (2.58)	2.112*** (3.24)	2.572*** (3.93)	3.186*** (4.73)	1.489*** (2.81)
pandemic2	1.428*** (2.84)	-1.091* (-1.82)	-0.785 (-1.24)	0.438 (0.67)	0.744 (1.12)	2.462*** (3.69)	3.077*** (4.52)	3.938*** (5.86)	4.495*** (6.66)	4.192*** (6.04)	1.974*** (3.62)
Wuhan * pandemic1	-4.664 (-0.79)	-12.804* (-1.81)	-14.058* (-1.89)	-14.795* (-1.92)	-13.442* (-1.71)	-10.971 (-1.39)	-9.357 (-1.17)	-7.672 (-0.97)	-6.107 (-0.77)	-5.244 (-0.64)	-10.056 (-1.63)
Wuhan * pandemic2	-4.664 (-0.79)	-12.804* (-1.81)	-13.24* (-1.78)	-14.795* (-1.92)	-13.169* (-1.68)	-10.971 (-1.39)	-9.357 (-1.17)	-5.217 (-0.66)	-6.107 (-0.77)	-5.244 (-0.64)	-9.455 (-1.54)
Hubei * pandemic1	-0.703 (-0.4)	-0.499 (-0.24)	0.076 (0.03)	-0.982 (-0.43)	-0.109 (-0.05)	-0.026 (-0.01)	-0.086 (-0.04)	-1.188 (-0.51)	-0.333 (-0.14)	-0.720 (-0.30)	-0.488 (-0.26)
Hubei * pandemic2	-0.692 (-0.39)	-0.499 (-0.24)	0.304 (0.14)	-0.343 (-0.15)	0.537 (0.23)	-0.026 (-0.01)	-0.075 (-0.03)	-0.421 (-0.18)	-0.322 (-0.14)	-0.627 (-0.26)	-0.216 (-0.11)
CapitalCircle * pandemic1	0.312 (0.18)	-0.370 (-0.18)	1.351 (0.64)	2.461 (1.12)	0.170 (0.08)	0.089 (0.04)	-0.742 (-0.32)	0.052 (0.02)	0.371 (0.16)	-0.314 (-0.13)	0.415 (0.23)
CapitalCircle * pandemic2	0.324 (0.19)	-0.37 (-0.18)	1.474 (0.69)	1.024 (0.47)	1.089 (0.49)	0.089 (0.04)	-0.731 (-0.32)	0.504 (0.22)	0.382 (0.17)	-0.221 (-0.09)	0.378 (0.21)
LevelShift	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Seasonality	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	7994	7994	7994	7994	7994	7994	7994	7994	7994	7994	7994
R^2	0.466	0.508	0.548	0.556	0.569	0.588	0.616	0.631	0.621	0.622	0.638

Panel 2 The pandemic's direct impact on the loan size

Treat * Post1	-0.040	-0.274	-0.086	-0.100	-0.015	-0.001	-0.0001	-0.225	0.065	4.312***	0.069
	(-0.16)	(-0.59)	(-0.16)	(-0.18)	(-0.04)	(-0.00)	(-0.00)	(-0.60)	(0.11)	(4.33)	(0.28)
Treat * Post2	0.108	0.464	-0.178	-0.376	0.206	0.034	0.033	-0.320	0.096	-11.290***	-0.508*
	(0.36)	(0.86)	(-0.28)	(-0.59)	(0.42)	(0.11)	(0.12)	(-0.73)	(0.15)	(-9.76)	(-1.77)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Within-month Cyclicality	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Within-week Cyclicality	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Spring FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	15022	15022	15022	15022	15022	15022	15022	15022	15022	15022	14950
R^2	0.329	0.214	0.165	0.182	0.147	0.091	0.075	0.182	0.219	0.429	0.332

This table reports the pandemic's impacts on the quantiles in loan size distribution and the average loan size. In each of Columns [1] - [10], the dependent variable is the *k*th percentile ($k \in \{5, 15... 95\}$) of the loan maturity distribution; in Column [11], the dependent variable is the average loan maturity.

Panel 1 reports the pandemic's comprehensive impact on the quantiles in loan size distribution and the average loan size as estimated by Model (7), which uses city-quarter data for the period from 2011 to 2020. All columns include the same set of controls as in Appendix V, Panel 3, the same setting of *LevelShift* as described in Appendix VI, and include *Seasonality*, year and city fixed effects. Coefficients of control variables, *Seasonality*, *LevelShift*, year and city fixed effects are not presented here, but can be offered on request. Distributions and standard errors are clustered at the city-quarter level, and t-statistics are given in parentheses.

Panel 2 reports the pandemic's direct impact on the quantiles in loan size distribution and the average loan size as estimated by Model (8), which uses city-day data from 01 December 2019 to 22 January 2020. All columns include the same set of explanatory variables. Year fixed effect, quarter fixed effects, within-month cyclicality, within-week cyclicality and the spring festival fixed effects are controlled. Coefficients of these fixed effects are not presented here but can be offered on request. Distributions and standard errors are clustered at the city-day level, and t-statistics are given in parentheses.

*p<0.10, **p<0.05, ***p<0.01

Table 14: Impacts of the Pandemic on Funded Marketplace Loan Maturities – Frequencies of k-month Loans

	3 month [1]	6 month [2]	9 month [3]	12 month [4]	24 month [5]	36 month [6]
Panel 1 The pandemic's comprehensive impact on the loan maturity						
pandemic1	350.961***	-823.601***	-699.659***	-99.427	102.919***	138.731***
	(3.44)	(-11.6)	(-3.74)	(-1.37)	(17.68)	(2.68)
pandemic2	560.480***	-705.965***	-908.360***	-22.820	33.901***	72.302
	(5.59)	(-9.3)	(-4.86)	(-0.31)	(5.58)	(1.34)
Wuhan * pandemic1	-2.034	-195.665	-539.671	-1408.107*	35.866	-1405.990***
	(0.00)	(-0.25)	(-0.34)	(-1.70)	(0.79)	(-3.54)
Wuhan * pandemic2	-1561.670	-1032.480	-2167.330	-349.198	-37.448	-1483.790***
	(-1.64)	(-1.31)	(-1.37)	(-0.42)	(-0.83)	(-3.69)
Hubei * pandemic1	-504.368*	-190.423	-651.459	-651.142***	-35.5623***	51.548
	(-1.66)	(-0.81)	(-1.33)	(-2.63)	(-2.63)	(0.39)
Hubei * pandemic2	-892.162***	-407.730*	-734.278	-852.362***	2.855	41.743
	(-2.94)	(-1.73)	(-1.49)	(-3.45)	(0.20)	(0.29)
CapitalCircle * pandemic1	1153.039***	453.4801*	1319.527***	1597.525***	82.075***	-105.505
	(3.60)	(1.94)	(2.87)	(6.74)	(6.24)	(-0.92)
CapitalCircle * pandemic2	1323.378***	576.818**	1225.554***	1717.550***	8.332	-162.417
	(4.13)	(2.47)	(2.67)	(7.25)	(0.63)	(-1.41)
LevelShift	Y	Y	Y	Y	Y	Y
Seasonality	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y	Y
Observations	2391	4364	2366	6156	4894	3946
R^2	0.599	0.502	0.604	0.455	0.507	0.564

Panel 2 The pandemic's direct impact on the loan maturity

Treat * Post1	3.422	-3.655**	0.204	-2.269	-0.350	3.051
	(1.64)	(-2.39)	(0.05)	(-1.14)	(-0.35)	(1.42)
Treat * Post2	10.546***	3.499**	-0.175	4.189*	0.660	-4.056
	(4.34)	(1.97)	(-0.04)	(1.81)	(0.59)	(-1.64)
Year FE	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y
Within-month Cyclicality	Y	Y	Y	Y	Y	Y
Within-week Cyclicality	Y	Y	Y	Y	Y	Y
Spring FE	Y	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y	Y
Observations	14307	14175	14839	14109	237	1185
R^2	0.924	0.928	0.938	0.936	0.466	0.775

This table reports the pandemic's impacts on the number of funded loans with different maturities. In each of Columns [1] - [6], the dependent variable is the number of loans with k-month maturity ($k \in \{3, 6, 9, 12, 24, 36\}$).

Panel 1 reports the pandemic's comprehensive impact on the number of funded loans with different maturities as estimated by Model (7), which uses city-quarter data for the period from 2011 to 2020. All columns include the same set of controls as in Appendix V, Panel 3, the same setting of *LevelShift* as described in Appendix VI, and include *Seasonality*, year and city fixed effects. Coefficients of control variables, *Seasonality*, *LevelShift*, year and city fixed effects are not presented here, but can be offered on request. Distributions and standard errors are clustered at the city-quarter level, and t-statistics are given in parentheses.

Panel 2 reports the pandemic's direct impact on the number of funded loans with different maturities as estimated by Model (8), which uses city-day data from 01 December 2019 to 22 January 2020. All columns include the same set of explanatory variables. Year fixed effect, quarter fixed effects, within-month cyclicality, within-week cyclicality and the spring festival fixed effects are controlled. Coefficients of these fixed effects are not presented here but can be offered on request. Distributions and standard errors are clustered at the city-day level, and t-statistics are given in parentheses.

*p<0.10, **p<0.05, ***p<0.01

4.5 Robustness Tests

I design two robustness tests in this section. The first robustness test examines the robustness of findings derived from baseline models, Model (7) and Model (8), which assume that time dummies can represent the dynamic impact of the pandemic. The second robustness test examines whether my inferred conclusions about P2P newcomers still hold after I manage to measure the indirect impact through data. I do not check whether my independent variables of interest are exogenous. The reason is that quarter dummies, city dummies, and the pandemic cases[39] applied are obviously exogenous. These variables are determined outside the economic and financial systems and can be treated as independent of any economic and financial factors. Some researchers also automatically treat these natural dimensions as exogenous. For example, Liu et al. (2018) study the influence of China's stimulus package during GFC on the lending behaviours of banks and investing behaviours of companies. They use a dummy variable to indicate the post-stimulus period and automatically treat it as exogenous.

4.5.1 The Robustness Test on the Effectiveness of Time Dummies

I hope to find alternative proxy variables to capture the pandemic's impacts. A natural candidate is the number of pandemic cases. I try possible options, such as accumulated confirmed cases, accumulated death cases, new confirmed cases, new death cases, and existing active cases. However, I immediately find that any cumulative values are unsuitable because they will never decrease. New confirmed cases and new death cases are typically a biased proxy of the pandemic's severity. Existing active cases may be the most suitable

[39] The pandemic cases are exogenous in my models based on three reasons: i) both the outbreak location of the pandemic and the movement of the population before lockdowns are randomized. ii) Governments of China have implemented highly unified and synchronized policies to control the virus, and these measurements are not based on economic and financial factors. More details are shown in the government document "Fighting Covid-19 China in Action". iii) The pandemic cases may relate to the population or its density, but I do not employ these control variables in my model.

alternative proxy. However, even existing cases do not perform well under Model (7). There are several potential reasons:

1) Existing cases at the end of a quarter cannot represent the pandemic's dynamic severity during the entire quarter.
2) Many cities stop publishing daily dynamics during the second quarter, so I cannot calculate the average existing cases of these cities during a quarter.
3) Existing cases may be an incomplete indicator of the pandemic's severity after the lockdowns and mobility restrictions, as physical restrictions added extra impacts to the economy, which cannot be effectively represented by existing cases.

As a result, I partially release my assumption in Model (8) by replacing Treat * Post interaction terms with the natural log of existing pandemic cases. I use the natural log of existing cases because the marginal influence of one existing case is negligible. My first robustness test model is:

$$y_{c,t} = \alpha_c + \beta ExistingCases_{c,t} + \gamma Cyclicality_c + \varepsilon_{c,t} \quad (9)$$

where *ExistingCases* is the natural log of daily active cases in a city. *Cyclicality* is a group of dummies designed to hold year fixed effects, quarter fixed effects, within-month cyclicality, within-week cyclicality and the spring festival fixed effects.

Results are listed in Panel 1 of Table 15 to Table 18. As shown, most results show the same patterns as the results derived by Model (8). It means that conclusions based on the results derived by Model (8) remain unchanged even if the assumption is removed.

4.5.2 The Robustness Test on the Pandemic's Indirect Impact on Lending Marketplaces through Banks

I have arguably inferred the influence of bank shutdown and the profiles of P2P newcomers from banks. Now I aim to measure the contribution of those newcomers through data. Ideally, I hope to find an event window when banks in some cities close while banks in

other cities remain open. Then I can compare these cities to extract the impact of bank shutdowns. Unfortunately, since almost all cities announced lockdowns and mobility restrictions during a very short period, I lost the opportunity to construct such a comparison. However, I find that the ending of lockdowns and mobility restrictions varied among cities, leaving me an opportunity to find the influence of banks reopening. Theoretically, the reopening and closing of banks have the opposite impacts, given that the lending market is liquid.

I use the intensity of intra-city travel shown in Figure 6 to measure the intensity of lockdowns and mobility restrictions. I compare Wuhan and cities outside Hubei to make the conclusion most significant. Figure 6 also helps me find a relatively accurate boundary of the event window, that is, from 23 January 2020 to 08 April 2020. My robustness test model 2 is:

$$y_{c,t} = \alpha_c + \beta Treat_c * Post_t * HighExistingCases_{c,t} + \gamma Cyclicality_c + \varepsilon_{c,t} \quad (10)$$

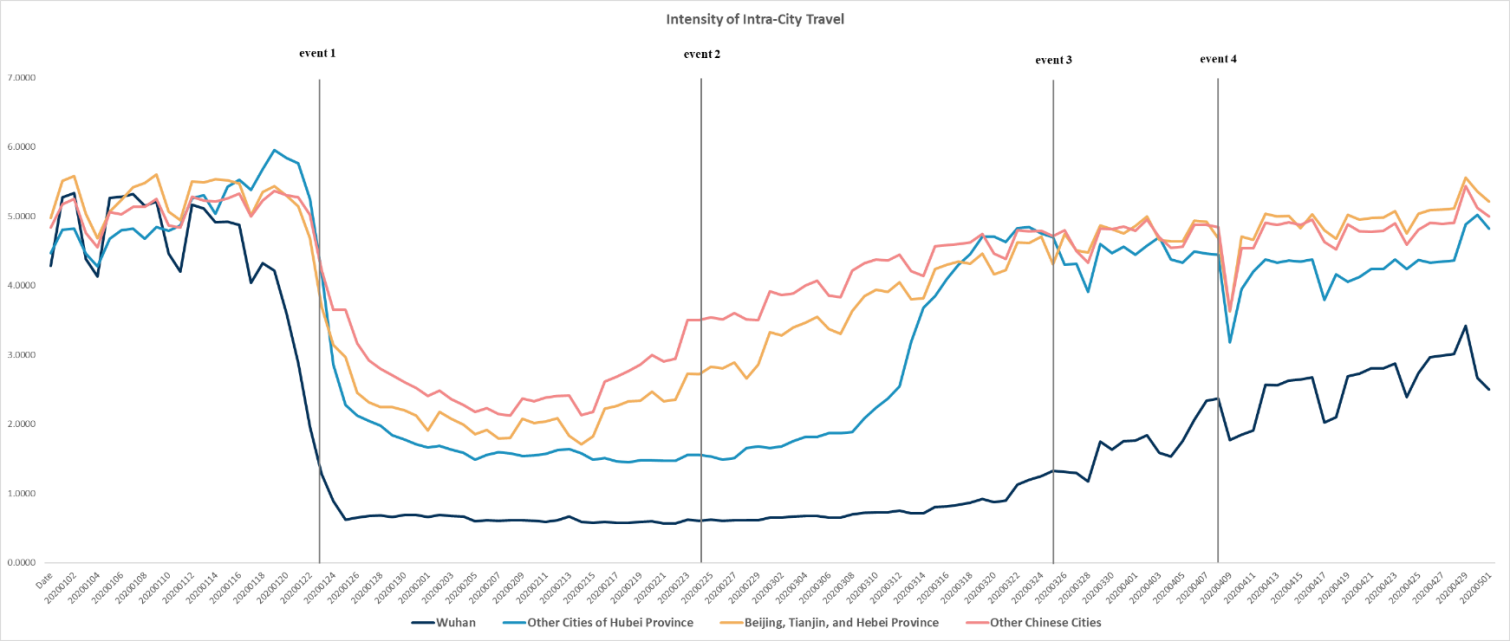
where *Treat* is a dummy variable equal to 1 if a city is outside Hubei and equal to 0 if it is Wuhan. *Post* equals 1 for the period after 24 February 2020, when most cities outside Hubei reopened while Wuhan kept locking down. *HighExistingCases* is a dummy variable indicating whether a city's current active cases were more than the median level. I use it to control for the severity of the pandemic because I aim to extract the pure impact of physical restriction and physical reopening. *Cyclicality* is a group of time dummies designed to hold year fixed effects, quarter fixed effects, within-month cyclicality, within-week cyclicality and spring festival fixed effects. Results are reported in Panel 2 of Table 15 to Table 18.

As shown, after banks reopened and some marketplace newcomers moved back to the banking sector, marketplace lending volume decreased, and the right tails of loan size distributions and loan maturity distributions tend to become thinner. Since banks reopening impacted the marketplace lending in an opposite way to banks closing, I can conclude that banks shutting down increased the marketplace lending volume. *Hypotheses H2a* and *H2b*

are supported. Marketplace newcomers from banks tended to borrow bigger-size and longer-maturity loans than pre-existing marketplace borrowers. *Hypothesis H3* is supported.

Figure 6: Intensity of Intra-City Travel

These data are collected from Baidu Migration Database[40]. The vertical axis is the magnitude of intra-city travel intensity, which is calculated as an indexed ratio of the number of people traveling within a city to the number of people living in the city. The horizontal axis shows the time span of the collected data, which is from 1 January 2020 to 1 May 2020. Event 1 represents a nationwide initiation of the first-level response to major public health emergencies. As shown, before the official announcement of the emergency response, most Chinese have begun to reduce their outgoing activities spontaneously. Event 2 refers to the point in time when cities outside the Beijing-Tianjin-Hebei region and Hubei lowered their level of emergency response. Based on government files, compared with other cities, governments in the Beijing-Tianjin-Hebei region have adopted stricter epidemic control measures. However, the intra-city intensity in the Beijing-Tianjin-Hebei region has shown a pattern similar to the average level of other cities across the country. Event 3 is the day when lockdowns of cities in Hubei except Wuhan were lifted. Event 4 is the unblocking date of Wuhan. The chart reveals that, for other cities in Hubei, a sharp recovery in terms of intra-city travel already occurred even before the lifting of lockdowns (event 3). The intra-city transportation in Wuhan also began to rise steadily and slowly before the official lifting (event 4).



[40] https://qianxi.baidu.com/

Table 15: Robustness Tests on Impacts of the Pandemic on Funded Marketplace Loan Volume

	Amount	Number
	[1]	[2]
Panel 1 Direct impact of the pandemic on funded P2P loan volume		
Existing Cases	-0.129***	-0.005
	(-5.52)	(-0.37)
Observations	14,950	14,950
R^2	0.822	0.886
Panel 2 Indirect Impact of the pandemic through Bank Reopening on P2P loan volume		
Treat * Post * HighExistingCases	-0.017	-0.014**
	(-1.63)	(-2.32)
Observations	21649	21649
R^2	0.769	0.887
Year Fixed Effect	Y	Y
Quarter Fixed Effect	Y	Y
Within-month Cyclicality	Y	Y
Within-week Cyclicality	Y	Y
Spring Festival Fixed Effect	Y	Y
City FE	Y	Y

This table reports the robustness tests on the pandemic's impacts on the volume of funded P2P loans.
Panel 1 shows the robustness test on the pandemic's direct impact on the volume. The direct impact is estimated by Model (9), which uses city-day data 01 December 2019 to 22 January 2020; Panel 2 shows the robustness test on the pandemic's indirect impact on the volume. The indirect impact is estimated by Model (10), which uses city-day data from 23 January 2020 to 08 April 2020.
The dependent variable is P2P origination volume. Funded volume is measured either by the total amount (Column [1]) or the total number of funded loans (Column [2]) per 10,000 residents in a given city. I further take a natural-log transformation for these dependent variables to enhance the explaining power of the model. All columns include the same set of explanatory variables. Year fixed effect, quarter fixed effects, within-month cyclicality, within-week cyclicality and the spring festival fixed effects are controlled. Coefficients of these fixed effects are not presented here but can be offered on request. Standard errors are clustered at the city-day level, and t-statistics are given in parentheses.
*p<0.10, **p<0.05, ***p<0.01

Table 16: Robustness Tests on Impacts of the Pandemic on Funded Marketplace Loan Sizes – Percentiles and Average

	5th [1]	15th [2]	25th [3]	35th [4]	45th [5]	55th [6]	65th [7]	75th [8]	85th [9]	95th [10]	Average [11]
Panel 1 Direct impact of the pandemic on funded P2P loan sizes – percentiles and average											
Existing Cases	-4.311	-5.982	-8.583	-29.403	-1.883	-4.466	-9.145	-34.727	-123.942	-6557.30***	-756.205***
	(-0.29)	(-0.36)	(-0.44)	(-1.14)	(-0.06)	(-0.11)	(-0.18)	(-0.44)	(-0.62)	(-10.14)	(-8.94)
Observations	15022	15022	15022	15022	15022	15022	15022	15022	15022	15022	15022
R^2	0.419	0.315	0.251	0.203	0.213	0.219	0.186	0.129	0.202	0.455	0.526
Panel 2 Indirect Impact of the pandemic through Bank Reopening on P2P loan sizes – percentiles and average											
Treat * Post *	6.419	-2.016	-8.639	-14.702	-47.933	-118.463***	-155.089***	-166.252***	-424.111***	-361.893*	--61.018*
HighExistingCases	(0.63)	(-0.19)	(-0.77)	(-1.10)	(-3.11)	(-3.68)	(-4.36)	(-3.24)	(-4.65)	(-1.67)	(-1.78)
Observations	21749	21749	21749	21749	21749	21749	21749	21749	21749	21749	21649
R^2	0.265	0.242	0.216	0.182	0.174	0.084	0.100	0.102	0.150	0.272	0.279
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Within-month Cyclicality	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Within-week Cyclicality	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Spring Festival FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

This table reports the robustness tests on the pandemic's impacts on the average of funded P2P loan sizes and the percentiles of funded P2P loan size distribution.

Panel 1 shows the robustness test on the pandemic's direct impact on the percentiles and average. The direct impact is estimated by Model (9), which uses city-day data from 01 December 2019 to 22 January 2020; Panel 2 shows the robustness test on the pandemic's indirect impact on the percentiles and average. The indirect impact is estimated by Model (10), which uses city-day data from 23 January 2020 to 08 April 2020.

In each of Columns [1] - [10], the dependent variable is the kth percentile ($k \in \{5, 15... 95\}$) of the loan size distribution; in Column [11], the dependent variable is the average loan size. All columns include the same set of explanatory variables. Year fixed effect, quarter fixed effects, within-month cyclicality, within-week cyclicality and the spring festival fixed effects are controlled. Coefficients of these fixed effects are not presented here but can be offered on request. Standard errors are clustered at the city-day level, and t-statistics are given in parentheses.

*p<0.10, **p<0.05, ***p<0.01

Table 17: Robustness Tests on Impacts of the Pandemic on Funded P2P Loan Maturities – Percentiles and Average

	5th [1]	15th [2]	25th [3]	35th [4]	45th [5]	55th [6]	65th [7]	75th [8]	85th [9]	95th [10]	Average [11]
Panel 1 Direct impact of the pandemic on funded P2P loan maturities – percentiles and average											
Existing Cases	0.014	0.071	-0.097	-0.175*	0.003	0.014	-0.015	-0.122*	0.015	-2.176***	-0.195***
	(0.29)	(0.82)	(-0.95)	(1.71)	(0.04)	(0.29)	(-0.33)	(-1.74)	(0.14)	(-11.96)	(-4.23)
Observations	15022	15022	15022	15022	15022	15022	15022	15022	15022	15022	14950
R^2	0.329	0.214	0.165	0.183	0.147	0.091	0.075	0.182	0.219	0.430	0.332
Panel 2 Indirect Impact of the pandemic through Bank Reopening on P2P loan maturities – percentiles and average											
Treat * Post *	-0.015*	-0.003	-0.016	-0.023	-0.022	-0.062***	-0.062***	0.006	-0.106***	-0.165***	-0.059**
HighExistingCases	(-1.83)	(-0.23)	(-0.94)	(-1.31)	(-1.56)	(-5.30)	(-4.87)	(0.42)	(-4.99)	(-3.30)	(-2.15)
Observations	21749	21749	21749	21749	21749	21749	21749	21749	21749	21749	21649
R^2	0.237	0.192	0.1609	0.152	0.133	0.080	0.168	0.241	0.114	0.247	0.247
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Within-month Cyclicality	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Within-week Cyclicality	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Spring Festival FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

This table reports the robustness tests on the pandemic's impacts on the average of funded P2P loan maturities and the percentiles of funded P2P loan maturity distribution. Panel 1 shows the robustness test on the pandemic's direct impact on the percentiles and average. The direct impact is estimated by Model (9), which uses city-day data from 01 December 2019 to 22 January 2020; Panel 2 shows the robustness test on the pandemic's indirect impact on the percentiles and average. The indirect impact is estimated by Model (10), which uses city-day data from 23 January 2020 to 08 April 2020.

In each of Columns [1] - [10], the dependent variable is the kth percentile ($k \in \{5, 15... 95\}$) of the loan maturity distribution; in Column [11], the dependent variable is the average loan maturity. All columns include the same set of explanatory variables. Year fixed effect, quarter fixed effects, within-month cyclicality, within-week cyclicality and the spring festival fixed effects are controlled. Coefficients of these fixed effects are not presented here but can be offered on request. Standard errors are clustered at the city-day level, and t-statistics are given in parentheses.

*p<0.10, **p<0.05, ***p<0.01

Table 18: Robustness Tests on Impacts of the Pandemic on Funded Marketplace Loan Maturities – Frequencies of k-month Loans

	3 month [1]	6 month [2]	9 month [3]	12 month [4]	24 month [5]	36 month [6]
Panel 1 Direct impact of the pandemic on funded P2P loan maturities – interval frequencies						
Existing Cases	3.274***	-1.899***	-4.633***	0.624*	0.111	-0.756
	(8.36)	(-6.62)	(-6.47)	(1.68)	(0.49)	(-1.51)
Observations	14307	14175	14839	14109	237	1185
R^2	0.925	0.928	0.938	0.936	0.466	0.775
Panel 2 Indirect Impact of the pandemic through Bank Reopening on P2P loan maturities – percentiles and average						
Treat * Post * High Existing Cases	2.072***	0.527***	0.392	4.340***	-0.3464***	-0.118
	(10.32)	(4.16)	(1.53)	(18.41)	(-3.49)	(-1.41)
Observations	20800	19506	21263	20546	7353	5259
R^2	0.893	0.856	0.898	0.888	0.639	0.590
Year Fixed Effect	Y	Y	Y	Y	Y	Y
Quarter Fixed Effect	Y	Y	Y	Y	Y	Y
Within-month Cyclicality	Y	Y	Y	Y	Y	Y
Within-week Cyclicality	Y	Y	Y	Y	Y	Y
Spring Festival Fixed Effect	Y	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y	Y

This table reports the robustness tests on the pandemic's impacts on the interval frequencies of the loan size distribution.

Panel 1 shows the robustness test on the pandemic's direct impact on the interval frequencies. The direct impact is estimated by Model (9), which uses city-day data from 01 December 2019 to 22 January 2020; Panel 2 shows the robustness test on the pandemic's indirect impact on the interval frequencies. The indirect impact is estimated by Model (10), which uses city-day data from 23 January 2020 to 08 April 2020.

In each of Columns [1] - [6], the dependent variable is the number of loans with k-month maturity ($k \in \{3, 6, 9, 12, 24, 36\}$). All columns include the same set of explanatory variables. Standard errors are clustered at the city-day level, and t-statistics are given in parentheses. Coefficients of these fixed effects are not presented here but can be offered on request.

*p<0.10, **p<0.05, ***p<0.01

4.5.3 Why are the Results Insensitive to the Supply Side of Credit?

Conclusions drawn from my measurement results are more valid when these results are not subject to the limit of credit supply. Theoretically, any limits from the supply side of credit should be reflected by an increase in loan rates or a decrease in origination volume, ceteris paribus. However, no such changes are found in my case. First, as mentioned before, loan rates are set by the platform based on borrower characteristics rather than priced by the market. Second, the previous analysis shows that the overall origination volume during the pandemic increased. These two facts together do not support the notion that substantive credit constraints happen. So, borrowers during the pandemic are likely to face at least a near-perfectly elastic credit supply. Other evidence is Appendix IV.4. As shown, the average time for loan projects being fully funded during the pre- and post-pandemic periods was less than twenty seconds, which means the marketplace credit market was highly liquid, and credit supply remained sufficient before and during the pandemic.

4.6 Chapter Conclusion and Policy Implications

By analysing a proprietary dataset, I examine the impact of the pandemic on lending marketplaces in China. I find that the pandemic's impact was a mixture of two effects. First, the pandemic had a direct impact on pre-existing marketplace borrowers. The borrowing activities of these pre-existing borrowers were inhibited by the pandemic. They tended to borrow more small-sized and short-term loans than the ex-ante level, and the change in their preference significantly altered the ex-ante distribution of loan sizes and loan maturities. Second, the pandemic also indirectly influenced the marketplace lending industry through marketplace newcomers from banks. Some bank-dependent borrowers could not be served by banks because of lockdowns and mobility restrictions; at least some of them were diverted away by marketplaces. The contribution of these marketplace newcomers was enormous, making the overall origination volume through platforms significantly increase. Large-sized

and long-term marketplace loans made during the outbreak of the pandemic in China were mainly contributed by these marketplace newcomers.

An interesting phenomenon is that the pandemic has inconsistently placed impacts on the loan volume, size, and maturity across the country. Specifically, the pandemic's comprehensive impact on the loan volume diminished significantly during 2020Q2, implying that the impact on the loan volume may be temporary instead of permanent. The pandemic's comprehensive impact on the average loan size reversed to an insignificant extent during the second quarter, but its comprehensive impact on the loan size distribution is further enhanced; the pandemic's comprehensive impacts on both the average loan maturity and the loan maturity distribution are further enhanced during the second quarter. So, at least in the first half of 2020, there is no significant evidence supporting that the pandemic's comprehensive impacts on loan size and loan maturity are temporary.

Another finding is the uneven impacts of the pandemic on different cities. The pandemic added some extra negative impacts on the borrowing volume in Wuhan and other Hubei cities. The pandemic added some extra negative impacts on the average loan maturity (insignificant) and the loan maturity distribution (significant) in Wuhan. By contrast, other Hubei cities are not subject to such extra impacts. The pandemic had not caused extra impacts on the average loan size and loan size distribution of Wuhan and other Hubei cities.

My findings imply that marketplaces might have some advantages over banks in supplying credit during the pandemic, as operation and credit-intermediation procedures of the marketplaces are entirely based on the internet. However, the absolute volume of the marketplace lending industry is negligible compared with banks. Commercial banks are still the dominant credit suppliers in China, so it is crucial for commercial banks to extend the application of FinTechs and develop more online options for borrowers.

5. Do China's Bank Stocks React to their Marketplace Lending Competitors?

5.1 Chapter Introduction

It is not known to what degree banks are affected overall by their marketplace lending competitors. An important reason is that the reactions of banks to these competitors are typically hard to observe when both banks and lending marketplaces are free from interventions and developing at their own pace as expected by the market. In this paper, I make use of the volatile policies of the Chinese government against lending marketplaces and manage to observe the reactions of bank stocks to these exogenous intensive interventions on competitors.

By studying these exogenous regulatory interventions in China, the paper aims to provide evidence regarding the market's opinion on whether lending marketplaces significantly affect the future value of banks and whether this effect is positive or negative. I carefully locate an *event period* and an *event point* based on the release dates of watershed documents indicating these disturbances. I then calculate the CARs of listed financial institutions around the events. Treating nonbank financial institutions as the control group, I get results strongly indicating that China's listed banks react to the turbulence encountered by their marketplace lending competitors, even though the current aggregated size of these competitors is still small.

Studies are generating mixed evidence on whether the global prosperity of lending marketplaces and other FinTech companies aggregately benefits or disturbs the future of traditional banks. The challenge is that a clear boundary between the banking industry and the FinTech industry no longer exists, as the latest technologies and innovative business models from the FinTech industry are introduced into the traditional banking industry (Stulz, 2019; Lee et al., 2021; Murinde et al., 2022). Therefore, it is necessary to separately consider the impact of the internal applications of these technologies and models by banks and the impact of external FinTech competition. On the one hand, extant literature recognises the

synergies brought by FinTech firms and documents that banks more adaptive to these new technologies and models perform better in multiple dimensions, such as profitability, cost efficiency, risk screening, and loan quality (Cheng and Qu, 2020; Lee et al., 2021). FinTech companies have more flexible organisations, shorter development cycles, and lower bureaucratic costs, making them constantly more responsive to cutting-edge technologies and models than banks (Ansari and Krop, 2012; Christensen, 2013; Phan et al., 2020; Elsaid, 2021). While FinTech companies grow by trial and error, banks can follow by picking successful cases. Thus, for banks, the synergies brought by FinTech companies may be sustainable. On the other hand, studies also find that external competition from FinTech companies is "disruptive" and negatively influences the performance of banks (Chen et al., 2019; Dong et al., 2020; Phan et al., 2020).

Our empirical results are consistent with the view that competition from FinTech firms outweighs the synergies they bring. To the best of our knowledge, the innovation of this study is threefold: i) it focuses on the net influence of FinTechs on banks; ii) it creatively treats China's volatile policies against bank competitors as exogenous shocks; iii) while most literature explores the accounting information of banks, this study develops from the perspective of stock market reactions, one of the most sensitive indicators of the net influence of shocks. I further run heterogeneity tests to analyse how banks with different attributes react differently to these exogenous shocks. Some heterogeneity tests show that their differential applications of FinTechs cannot effectively explain their heterogeneous stock reactions, implying that banks do not face technical barriers when competing with lending marketplaces. Instead, I find results supporting their potential disadvantages are likely to be adherence to field operations and heavier regulatory burdens. For each heterogeneity test, I use multiple proxy variables to measure one bank attribute of interest and enhance the robustness of our results. Finally, I run an endogeneity test showing that the uninterrupted growth of lending marketplaces before the sanction has not impacted the financial health of

banks. The results largely reduce the likelihood that the government cracked down on lending marketplaces due to “bank protectionism” or other implicit guarantees to banks, making these events exogenous to the banking sector.

The remainder of the paper is organised as follows. Section 5.2 introduces the reasons for the emergence and disorder of China’s lending marketplaces and derives the government’s motivation for vigorous rectification. Section 5.3 explains the approach of variable construction, the data, and the methodology used. Empirical results are presented and discussed in Section 5.4. Section 5.4 also deals with heterogeneity testing and endogeneity testing. Section 5.5 concludes the paper.

5.2 Institutional Backgrounds

5.2.1 The Underdeveloped Financial Market, Bank Inefficiency, and Credit Misallocation

The financial market in China is dominated by banks, especially SOCBs, and the stock and bond markets are underdeveloped (Allen et al., 2005). Unlike SOEs or listed firms with broader access to equity and bond financing, firms in the private sector are usually limited to bank credit and other informal credit (Ayyagari et al., 2010). However, the banking system in China, especially SOCBs, has long been subject to operational inefficiency (e.g., see Fu and Heffernan, 2007; Kumbhakar and Wang, 2007; Shih et al., 2007; Ariff and Luc, 2008; Berger et al., 2009; Yin et al., 2013; Zhang et al., 2020). Extant literature also well documents credit misallocation by banks and their strong tendency to extend credit to SOEs and large private firms (e.g., see Firth et al., 2009; Cong et al., 2019). These features create substantial obstacles for most private SMEs in obtaining enough credit from the formal financial sector (Chong et al., 2013; Ma et al., 2019). The banking system also has similar inefficiency in providing enough credit to individuals and households for their expenses, home ownership, and entrepreneurship (Li and Yi, 2007; Zhou, 2014; He and Li, 2021). Moreover, the formal financial market in China does not provide enough investment opportunities to satisfy the

grown appetite of the middle class (Elliott et al., 2015; Lu et al., 2015; He and Li, 2021). All of these disadvantages greatly necessitate the development of the marketplace lending industry, both as an alternative financing resource and as an innovative investment tool.

5.2.2 Lending Marketplaces Failures and Volatile Regulation Environment

The growth of China's marketplace lending industry was far ahead of the construction of the related regulation framework, leaving the entire industry a huge space for regulatory arbitrage. The first lending marketplace in China was PPDai.com, which launched in June 2007. The industry reached a trading volume of RMB 245.3 billion with 2,238 platforms by the end of 2014.[41] After seven years of unregulated development, the first supportive guide was enacted in July 2015[42], in which no explicit restrictions on operation models were clearly discussed. I find that the first restrictive guide, "*Opinions by the State Council of Further Effectively Preventing and Disposing of Illegal Fundraising*", was not in position until February 2016. The long-term absence of regulations and laws regarding operation qualifications, operation paradigms, and misconduct penalties has multiple consequences. First, to maintain competitiveness and maximize profitability, lending marketplaces in China have quickly evolved from a pure credit intermediary to various riskier forms, such as the guarantee of principal for lenders, the promise of high returns, the issuance of wealth management products, and the formation of fund pools (Balyuk and Davydenko, 2019; Li et al., 2020; Jiang et al., 2021). Second, many unqualified platforms, typically those with insufficient registered capital, had entered this industry. Their survival is highly vulnerable to borrower defaults due to the risky operations mentioned above and the lack of solid safety nets. Third, the unregulated environment also bred fraudulent behaviours, such as fake projects and Ponzi schemes (He and Li, 2021; Jiang et al., 2021). The massive failures of

[41] I use the estimation from Frost & Sullivan.

http://www.frostchina.com/wp-content/uploads/2019/05/P2Pjiedai.pdf

[42] I systematically searched and sorted all related guidance and policy documents by issuance date from PKULAW, the most comprehensive database specialised in the document collection of laws and regulations of China. The title of the guide is "*Guiding Opinions on Promoting the Healthy Development of Internet Finance*". Following regulation documents mentioned in this paper are also from this database.

platforms caused substantial losses to millions of investors' savings, which in turn led to systemic financial risks and social instability.

The large-scale collapse quickly reversed the official attitude towards the industry. The long-term absence of regulations was stiffly compensated by piecemeal measures from the government, such as the sudden halt in industry entry, intensive rectification, and the intention to minimise the industry in the following years. On 21 November 2017, the government issued the "*Notice on the Immediate Suspension of the Approval of Online Microfinance Companies*".[43] The government prohibited new competitors from entering the marketplace lending industry as too much risk existed in the "*cash loans*"[44] issued by platforms. The prohibition largely limited the further growth of the industry. On 08 December 2017, the government issued the "*Implementation Plan for the Special Rectification of Risks in the Online Microloan Business of Microfinance Companies*" and the "*Notice on Doing a Good Job in the Special Rectification, Reconstruction, and Acceptance Test of Risks in P2P Online Lending*", which signalled the nationwide review of qualifications and operations of established platforms. Based on review reports, regulators might certify, rectify, or ban platforms. By this time, the common public perception was that the industry would shrink in the future, yet the financial market still believed that, as stated in the plan and the notice, regulators were leaving chances of normal operation for qualified platforms. However, on 19 December 2018, regulators shifted their attitude towards the industry again. In the document "*Opinions on Doing a Good Job in the Disposal of Online Lending Institutions by Classifications and the Risk Prevention of Online Lending Institutions*", the government set the compulsory withdrawal of platforms as the primary

[43] Strictly speaking, microfinance companies provide microloans to borrowers using their own funds, which is different from lending marketplaces where the credit is directly from investors. However, I find that the Chinese government usually treats lending marketplaces as a subtype of microfinance companies and applies uniform measures to these institutions.

[44] Based on several documents issued by regulators, they define "*cash loans*" as unconditional loans that do not specify borrowers' features, situations, or purposes, do not require collateral, and directly pay cash to borrowers. According to this definition, marketplace loans are a kind of "*cash loans*".

strategy. Even for strictly qualified platforms, the government added heavy limits on the maximum volume of credit that could be mediated and proactively persuaded these platforms to transform into online microloan companies that only use their own funds instead of money from retail investors. The financial market realised that the government's determination to eliminate the risk was probably underestimated before, and lending marketplaces in China could eventually disappear.

5.3 Research Design and Data Construction

I am inspired by a strand of literature studying the wealth effects of macro policies on stocks of related banks and other related companies (e.g., see Chen, 2007; Berkman et al., 2010; Wang et al., 2018; Yang and He, 2019; Demirgüç-Kunt et al., 2021). I use an event study technique (Brown and Warner, 1985; Kolari and Pynnönen, 2010) to test the effect of adverse policy announcements regarding the marketplace lending industry on the stock returns of banks in China. The study also assesses whether heterogeneous reactions by banks to these adverse policies convey new information about their ability to effectively compete with lending marketplaces before the government's interventions incur industry-level recession for their competitors.

I locate an *event period* and an *event point* based on the issuance dates of watershed documents described in Section 5.2 and the work of He and Li (2021). They find that political factors largely account for the failures of lending marketplaces in China. More specifically, they show that during the twelve months before the 19th National Congress of the Communist Party of China (from 18 to 24 October 2017)[45], failing platforms are much less likely to declare bankruptcy or run off than after the congress, as politicians have strong incentives to suppress negative information (Piotroski et al., 2015) and avoid large-scale

[45] The National Congress is the highest authority of the Communist Party of China and convenes every five years. The congress elects the leading bodies of the Communist Party, outlines policies of the central government, and sets political and economic objectives for the following five years.

social instability before major political events. Their finding is consistent with the timing of intensive promulgation of heavily restrictive documents at the end of 2017, which accelerated the sweeping of platforms. Thus, the first *event period* is from 18 October to 08 December 2017. The second *event point*, 19 December 2018, indicates the date when the public realised that the entire marketplace lending industry could disappear.

I first apply the standard market model to calculate the market reactions to the issuance of adverse policies. The estimation window is from 130 days to 30 days before the *event period* and the *event point*. Only shares with at least 60 trading days in the estimation window are included. I calculate the abnormal return (AR) of each share as:

$$AR_{i,t} = R_{i,t} - \widehat{R_{\iota,t}} = R_{i,t} - (\alpha + \beta R_{m,i,t}) \qquad (11)$$

where $R_{i,t}$ is the realised return of share i at time t, $\widehat{R_{\iota,t}}$ is the predicted return of share i at time t by the standard market model, and $R_{m,i,t}$ is the realised return of the market where share i is traded. α and β are estimated during periods from 130 days to 30 days before the *event period* and the *event point*.

In order to capture market reactions in the short-, the medium-, and the long-term, I look into multiple windows of CARs of 3 days (*CAR [–1, +1*]), 5 days (*CAR [–2, +2]*), 11 days (*CAR [–5, +5]*), 1 month (*CAR [+1, +30]*), 3 months (*CAR [+1, +90]*), and 1 year (*CAR [+1, +365]*). I also include *CAR [–30, –1]* and *CAR [–5, –1]* to represent the ex-ante benchmark performance of shares.

$$CAR_{i,t} = \sum AR_{i,t} \qquad (12)$$

I collect the stock prices of banks and nonbank financial institutions listed in the mainland A-share markets around the *event period* and the *event point*. I choose to compare the performance of listed banks with listed nonbank financial institutions instead of companies in other industries for several reasons: i) the finance industry is specially regulated, so it makes

more sense to compare shares within the finance industry; ii) Although the regulatory details of banks and nonbank institutions are still different, I find their regulatory environment remains qualitatively unchanged during the periods I studied after systematically checking the PKULAW database; iii) I largely avoid the possibility that unknown confounding factors happen to impact the entire finance industry if the comparison is within the industry and stock prices of banks and nonbank financial institutions do not comove.

In the mainland, there are 25 (26) bank shares and 58 (63) nonbank financial institution shares with more than 60 trading days during the estimation window before the *event period* (the *event point*). In Hong Kong, there are 22 (26) bank shares[46] and 185 (197) nonbank financial institution shares with more than 60 trading days during the estimation window before the *event* period (the *event point*). For stocks listed in the mainland (Hong Kong), I use the capitalisation-weighted market index, CSI 300 (HSI)[47], to measure the market return.

5.4 Empirical Results and Explanations

5.4.1 Main Results

5.4.1.1 Results Based on the Standard Market Model

Table 19 displays the CARs of formal financial institutions across different event windows around the *event period* and the *event point*. Panel A shows that the share performance of nonbank financial institutions is invariant to the intensive issuance of restrictive documents during the *event period*. Also, their share performance is constantly and significantly below the predicted performance by the standard market model. By contrast, the performance of bank stocks fluctuates. Bank stocks have significant and negative CARs before the *event period* (*CAR [–30, –1]* and *CAR [–5, –1]*). Their performance is not significantly deviated

[46] For banks listed in Hong Kong, I only select those banks whose main business is in the mainland. Some banks in China use dual listing strategy to expand their investor base. I treat their listings in different exchanges separately.

[47] The CSI 300 is a capitalisation-weighted stock market index designed to replicate the performance of the top 300 stocks traded on the Shanghai Stock Exchange and the Shenzhen Stock Exchange. The Hang Seng Index (HSI) is a capitalisation-weighted stock market index designed to replicate the portfolio performance of the largest companies traded in the Stock Exchange of Hong Kong.

from the model prediction near the *event period* (*CAR [–5, +5]*, *CAR [–3, +3]*, *CAR [–1, +1]*, *CAR [0]*, and *CAR [+1, +5])*. Bank stocks start to show medium-term positive and significant deviations from the model prediction (*CAR [+1, +30]* and *CAR [+1, +90]*). However, such positive and significant deviations disappear in the long-term (*CAR [+1, + 365]*).

Panel B shows qualitatively consistent results. For nonbank financial institutions, the negative deviations became insignificant near the *event point* (*CAR [–1, +1]*, *CAR [0]*, and *CAR [+1, +5]*). Compared with Panel A, bank stocks overall show a greater amount of positive CARs after the *event point*. However, these positive CARs are not constantly significant. Like Panel A, such positive deviations disappear in the long-term (*CAR [+1, + 365]*).

Two panels reveal that banks and nonbank financial institutions react differently to adverse policies against the marketplace lending industry. Overall, although stocks of nonbank financial institutions show constant and negative deviations during the study period, they act insensitively to these adverse policies. By contrast, bank stocks have positive reactions to these adverse policies, implying the market values the suppressed development of lending marketplaces as good news for the future of banks.

Table 19: A-share Market Reactions to Adverse Policy Announcements against Lending Marketplaces

This table reports the CAR statistics of stock reactions of formal financial institutions listed in the mainland A-share Market. I use the standard market model based on the market index CSI 300 to calculate the abnormal returns of each stock during event windows. CARs are winsorized at the 5% and the 95% percentile. *, **, and *** are statistical significances at the 10%, 5%, and 1% level, respectively.

Panel A. The Event Period: 18 October 2017 – 08 December 2017

Banks								*Other Financial Institutions*							
Event Window	S. E.	Min.	Mean	Med.	Max.	*t*-stat	N	Event Window	S. E.	Min.	Mean	Med.	Max.	*t*-stat	N
CAR [–30, –1]	0.009	–0.175	–0.032***	–0.022	0.008	–3.393	25	*CAR [–30, –1]*	0.007	–0.175	–0.067***	–0.058	0.008	–10.152	58
CAR [–5, –1]	0.002	–0.024	–0.007***	–0.009	0.022	–3.230	25	*CAR [–5, –1]*	0.003	–0.076	–0.034***	–0.033	0.022	–9.685	58
CAR [–5, +5]	0.012	–0.131	–0.008	–0.005	0.096	–0.669	25	*CAR [–5, +5]*	0.017	–0.360	–0.171***	–0.175	0.079	–10.118	58
CAR [–3, +3]	0.013	–0.126	–0.002	0.009	0.104	–0.180	25	*CAR [–3, +3]*	0.015	–0.361	–0.167***	–0.170	0.038	–10.844	58
CAR [–1, +1]	0.012	–0.119	0.003	0.019	0.117	0.280	25	*CAR [–1, +1]*	0.016	–0.352	–0.149***	–0.141	0.064	–9.490	58
CAR [0]	0.002	–0.014	0.000	–0.002	0.019	0.084	25	*CAR [0]*	0.002	–0.022	–0.005***	–0.009	0.027	–2.755	58
CAR [+1, +5]	0.003	–0.029	0.001	0.004	0.025	0.227	25	*CAR [+1, +5]*	0.003	–0.050	–0.014***	–0.014	0.023	–4.592	58
CAR [+1, +30]	0.008	–0.068	0.012*	–0.002	0.076	1.486	25	*CAR [+1, +30]*	0.008	–0.172	–0.075***	–0.087	0.053	–9.602	58
CAR [+1, +90]	0.015	–0.201	0.032**	0.019	0.123	2.098	25	*CAR [+1, +90]*	0.015	–0.312	–0.143***	–0.160	0.123	–9.597	58
CAR [+1, +365]	0.069	–0.636	0.027	0.020	0.540	0.390	25	*CAR [+1, +365]*	0.048	–0.888	–0.092**	–0.025	0.609	–1.904	58

Panel B. The Event Point: 19 December 2018

Banks							
Event Window	S. E.	Min.	Mean	Med.	Max.	*t*-stat	N
CAR [–30, –1]	0.007	–0.128	–0.027***	–0.025	0.018	–3.920	26
CAR [–5, –1]	0.002	–0.017	0.002	0.002	0.016	0.809	26
CAR [–5, +5]	0.005	–0.038	0.010**	0.010	0.048	2.031	26
CAR [–3, +3]	0.004	–0.025	0.005*	0.006	0.042	1.374	26
CAR [–1, +1]	0.003	–0.021	0.001	0.003	0.033	0.480	26
CAR [0]	0.001	–0.011	0.002**	0.003	0.009	1.980	26
CAR [+1, +5]	0.004	–0.036	0.003	0.006	0.037	0.739	26
CAR [+1, +30]	0.006	–0.084	0.008*	0.011	0.054	1.398	26
CAR [+1, +90]	0.013	–0.068	0.022**	0.007	0.156	1.762	26
CAR [+1, +365]	0.055	–0.671	–0.016	0.020	0.489	–0.284	26

Other Financial Institutions							
Event Window	S. E.	Min.	Mean	Med.	Max.	*t*-stat	N
CAR [–30, –1]	0.008	–0.260	–0.117***	–0.109	0.018	–14.148	63
CAR [–5, –1]	0.002	–0.040	–0.013***	–0.016	0.016	–6.497	63
CAR [–5, +5]	0.003	–0.058	–0.011***	–0.007	0.027	–3.484	63
CAR [–3, +3]	0.003	–0.055	–0.004*	–0.007	0.042	–1.323	63
CAR [–1, +1]	0.002	–0.045	–0.001	0.001	0.028	–0.339	63
CAR [0]	0.001	–0.014	–0.001	–0.001	0.013	–0.541	63
CAR [+1, +5]	0.002	–0.052	0.001	0.004	0.029	0.421	63
CAR [+1, +30]	0.006	–0.126	–0.032***	–0.028	0.048	–5.259	63
CAR [+1, +90]	0.017	–0.210	–0.027*	–0.051	0.296	–0.064	63
CAR [+1, +365]	0.052	–1.104	–0.519***	–0.537	0.342	–10.019	63

5.4.1.2 Results Based on the Adjusted Market Model

Most formal financial institutions in China are state-owned, so constant and negative CARs of nonbank financial stocks in Table 19 show the potential pricing ineffectiveness of state-owned enterprises listed on the mainland stock market (Allen et al., 2005; Carpenter et al., 2021). The more worrying problem is to what degree this potential ineffectiveness distorts the performance of bank stocks. To mitigate the threat of the potential ineffectiveness to the study's robustness, I follow the study of Demirgüç-Kunt et al. (2021) and adjust the standard market model by employing a submarket index, CSI 000818[48], to account for unique information of the finance industry uncaptured by CSI 300. As shown in Table 20, constant and negative CARs of nonbank financial institutions are largely alleviated compared with the standard market model in Table 19. More importantly, I observe bank stocks have more stable ex-post reactions, i.e., constantly significant and positive CARs in the short- and medium-term after the *event period* and the *event point*. Like Table 19, the long-term CARs (*CAR [+1, + 365]*) of bank stocks become insignificant.

[48] CSI 000818 selects listed banks, insurance companies, securities companies, and trust companies as the index sample to reflect the overall performance of the finance industry on the Shanghai and Shenzhen Stock Exchanges.

Table 20: A-share Market Reactions to Adverse Policy Announcements against Lending Marketplaces: Adjusted Market Model

This table reports the CAR statistics of stock reactions of formal financial institutions listed in the mainland A-share Market. I use the adjusted market model based on the market index CSI 300 and the financial submarket index CSI 000818 to calculate the abnormal returns of each stock during event windows. CARs are winsorized at the 5% and the 95% percentile. *, **, and *** are statistical significances at the 10%, 5%, and 1% level, respectively.

Panel A. The Event Period: 18 October 2017 – 08 December 2017

Banks								*Other Financial Institutions*							
Event Window	S. E.	Min.	Mean	Med.	Max.	*t*-stat	N	Event Window	S. E.	Min.	Mean	Med.	Max.	*t*-stat	N
CAR [–30, –1]	0.010	–0.161	–0.013*	–0.004	0.029	–1.385	25	*CAR [–30, –1]*	0.007	–0.116	–0.010*	–0.001	0.074	–1.470	58
CAR [–5, –1]	0.002	–0.017	–0.001	–0.004	0.026	–0.274	25	*CAR [–5, –1]*	0.003	–0.046	–0.003	–0.002	0.049	–0.941	58
CAR [–5, +5]	0.012	–0.102	0.027**	0.032	0.129	2.242	25	*CAR [–5, +5]*	0.017	–0.203	–0.014	–0.015	0.234	–0.859	58
CAR [–3, +3]	0.013	–0.109	0.020*	0.033	0.125	1.563	25	*CAR [–3, +3]*	0.015	–0.208	–0.014	–0.015	0.196	–0.909	58
CAR [–1, +1]	0.012	–0.105	0.019*	0.033	0.132	1.508	25	*CAR [–1, +1]*	0.016	–0.217	–0.012	–0.002	0.191	–0.742	58
CAR [0]	0.002	–0.012	0.002*	0.000	0.021	1.325	25	*CAR [0]*	0.002	–0.017	–0.001	–0.005	0.034	–0.537	58
CAR [+1, +5]	0.003	–0.033	0.006**	0.007	0.029	2.099	25	*CAR [+1, +5]*	0.002	–0.032	0.000	–0.002	0.035	–0.161	58
CAR [+1, +30]	0.006	–0.031	0.037***	0.028	0.083	5.837	25	*CAR [+1, +30]*	0.008	–0.097	–0.003	–0.013	0.148	–0.431	58
CAR [+1, +90]	0.015	–0.158	0.069***	0.067	0.153	4.731	25	*CAR [+1, +90]*	0.016	–0.215	–0.022*	–0.032	0.274	–1.426	58
CAR [+1, +365]	0.072	–0.662	0.023	0.009	0.562	0.326	25	*CAR [+1, +365]*	0.046	–0.810	–0.072*	–0.021	0.576	–1.577	58

Panel B. The Event Point: 19 December 2018

Banks								*Other Financial Institutions*							
Event Window	S. E.	Min.	Mean	Med.	Max.	*t*-stat	N	Event Window	S. E.	Min.	Mean	Med.	Max.	*t*-stat	N
CAR [–30, –1]	0.007	–0.064	0.006	0.004	0.056	0.859	26	*CAR [–30, –1]*	0.008	–0.117	–0.006	–0.007	0.142	–0.741	63
CAR [–5, –1]	0.002	–0.016	0.001	0.001	0.014	0.641	26	*CAR [–5, –1]*	0.002	–0.028	0.000	–0.002	0.028	–0.204	63
CAR [–5, +5]	0.005	–0.038	0.013***	0.012	0.055	2.495	26	*CAR [–5, +5]*	0.003	–0.045	0.002	0.002	0.048	0.670	63
CAR [–3, +3]	0.004	–0.020	0.009**	0.006	0.058	2.279	26	*CAR [–3, +3]*	0.003	–0.044	0.003	–0.001	0.055	0.768	63
CAR [–1, +1]	0.003	–0.014	0.007**	0.008	0.044	2.403	26	*CAR [–1, +1]*	0.002	–0.040	0.001	0.002	0.034	0.355	63
CAR [0]	0.001	–0.011	0.002**	0.003	0.010	2.353	26	*CAR [0]*	0.001	–0.013	0.001	0.000	0.014	0.741	63
CAR [+1, +5]	0.004	–0.018	0.015***	0.016	0.059	3.598	26	*CAR [+1, +5]*	0.003	–0.041	0.002	0.002	0.035	0.615	63
CAR [+1, +30]	0.005	–0.071	0.016***	0.018	0.060	2.856	26	*CAR [+1, +30]*	0.006	–0.088	–0.003	–0.004	0.094	–0.467	63
CAR [+1, +90]	0.010	–0.048	0.021**	0.012	0.148	2.097	26	*CAR [+1, +90]*	0.015	–0.145	0.012	0.003	0.289	0.803	63
CAR [+1, +365]	0.041	–0.313	0.022	–0.002	0.416	0.546	26	*CAR [+1, +365]*	0.044	–0.532	–0.062*	–0.123	0.632	–1.409	63

5.4.1.3 Results Based on the Sample from the Stock Exchange of Hong Kong

Another threat to the study's robustness is the small sample size. I expand the sample by considering mainland commercial banks listed on the Stock Exchange of Hong Kong. I use the standard market model based on the market index HSI and get results qualitatively consistent with the behaviours of financial stocks listed on the Shanghai and Shenzhen Stock exchanges. Table 21 also implies that the Hong Kong stock market may price financial stocks more effectively as the standard market model has equivalent performance to the adjusted market model in Table 20.

Table 21: Hong Kong Market Reactions to Adverse Policy Announcements against Lending Marketplaces

This table reports the CAR statistics of stock reactions of formal financial institutions listed in the Stock Exchange of Hong Kong. I use the market model based on the market index HSI to calculate the abnormal returns of each stock during event windows. Banks in Panel A and Panel B are those whose main business is in the mainland. CARs are winsorized at the 5% and the 95% percentile. *, **, and *** are statistical significances at the 10%, 5%, and 1% level, respectively.

Panel A. The Event Period: 18 October 2017 – 08 December 2017

Banks							
Event Window	S. E.	Min.	Mean	Med.	Max.	*t*-stat	N
CAR [–30, –1]	0.006	–0.047	0.007	0.004	0.063	1.054	22
CAR [–5, –1]	0.003	–0.028	0.000	0.003	0.022	0.116	22
CAR [–5, +5]	0.017	–0.119	0.037**	0.023	0.194	2.211	22
CAR [–3, +3]	0.014	–0.082	0.020*	0.006	0.207	1.375	22
CAR [–1, +1]	0.016	–0.068	0.022*	–0.005	0.266	1.382	22
CAR [0]	0.002	–0.016	–0.002	–0.002	0.008	–1.314	22
CAR [+1, +5]	0.008	–0.087	0.013*	0.015	0.101	1.511	22
CAR [+1, +30]	0.014	–0.160	0.035**	0.038	0.182	2.500	22
CAR [+1, +90]	0.022	–0.212	0.050**	0.061	0.194	2.344	22
CAR [+1, +365]	0.037	–0.310	0.029	0.049	0.357	0.786	22

Other Financial Institutions							
Event Window	S. E.	Min.	Mean	Med.	Max.	*t*-stat	N
CAR [–30, –1]	0.009	–0.198	0.005	–0.019	0.318	0.585	185
CAR [–5, –1]	0.003	–0.063	0.001	–0.009	0.123	0.393	185
CAR [–5, +5]	0.014	–0.347	–0.001	–0.024	0.462	–0.083	185
CAR [–3, +3]	0.013	–0.328	–0.012	–0.033	0.392	–0.924	185
CAR [–1, +1]	0.013	–0.317	–0.018*	–0.045	0.383	–1.438	185
CAR [0]	0.002	–0.036	–0.001	–0.004	0.053	–0.497	185
CAR [+1, +5]	0.003	–0.099	–0.003	–0.003	0.089	–0.904	185
CAR [+1, +30]	0.008	–0.196	0.002	–0.011	0.235	0.306	185
CAR [+1, +90]	0.017	–0.382	0.009	–0.034	0.556	0.530	185
CAR [+1, +365]	0.055	–1.517	0.043	0.015	1.672	0.774	185

Panel B. The Event Point: 19 December 2018

Banks							
Event Window	S. E.	Min.	Mean	Med.	Max.	*t*-stat	N
CAR [–30, –1]	0.016	–0.279	–0.047***	-0.053	0.151	-2.894	26
CAR [–5, –1]	0.005	–0.084	–0.009**	-0.006	0.032	-1.998	26
CAR [–5, +5]	0.012	–0.087	0.020**	0.011	0.174	1.719	26
CAR [–3, +3]	0.007	–0.064	0.011*	0.012	0.074	1.621	26
CAR [–1, +1]	0.004	–0.042	0.006*	0.011	0.047	1.467	26
CAR [0]	0.002	–0.025	0.003*	0.005	0.028	1.362	26
CAR [+1, +5]	0.010	–0.092	0.013*	0.004	0.137	1.320	26
CAR [+1, +30]	0.012	–0.136	0.019*	0.027	0.140	1.516	26
CAR [+1, +90]	0.025	–0.302	0.048**	0.048	0.358	1.947	26
CAR [+1, +365]	0.084	–1.128	–0.044	-0.016	1.191	-0.521	26

Other Financial Institutions							
Event Window	S. E.	Min.	Mean	Med.	Max.	*t*-stat	N
CAR [–30, –1]	0.008	–0.239	–0.008	–0.009	0.216	–0.980	197
CAR [–5, –1]	0.004	–0.087	–0.003	–0.002	0.106	–0.944	197
CAR [–5, +5]	0.006	–0.143	–0.008*	–0.007	0.157	–1.501	197
CAR [–3, +3]	0.004	–0.103	–0.004	–0.002	0.141	–0.801	197
CAR [–1, +1]	0.003	–0.066	–0.001	0.002	0.078	–0.454	197
CAR [0]	0.001	–0.031	–0.001	–0.001	0.042	–0.920	197
CAR [+1, +5]	0.004	–0.098	–0.003	0.000	0.131	–0.685	197
CAR [+1, +30]	0.007	–0.178	–0.006	–0.004	0.216	–0.780	197
CAR [+1, +90]	0.018	–0.429	0.017	0.014	0.499	0.960	197
CAR [+1, +365]	0.050	–1.244	0.072*	0.019	1.439	1.453	197

5.4.2 Heterogeneity Tests

5.4.2.1 Potential Disadvantage I: Fixed-asset-heavy Business Model

Compared with lending marketplaces, listed banks have much larger fixed assets, which are currently less efficiently used. These fixed assets, such as lands, buildings, equipment, and other infrastructures used to establish physical branches, represent the legacy of their on-site way of facilitating credit before the massive applications of the internet. Physical branches are still essential for banks, especially small banks, to conduct firm lending, as evidenced by continuing literature (e.g., see Petersen and Rajan, 1995; Berger et al., 2005; Degryse and Ongena, 2005; Brevoort and Hannan, 2006; Alessandrini et al., 2009; Agarwal and Hauswald, 2010; Knyazeva and Knyazeva, 2012; Levine et al., 2020). However, physical branches and fixed assets attached to them have been much less important for modern consumption loans, which mainly rely on remote verification of personal income and credit history through databases, electronic documents, and digital footprints (Berg et al., 2020). Thus, some of the fixed assets of banks reflect a deviation from the modern way of channelling personal credit and may induce inefficiency. I treat some of these fixed assets as a potential disadvantage when competing with lending marketplaces, which do not have physical branches and completely mediate credit online.

I measure this potential disadvantage by calculating the proportional fixed assets of banks designated to serve the personal business. I propose two practical solutions below:

$$CAR_{i,t} = \alpha_m + \sigma_t + \beta_1 ln(TA_{i,t}) + \beta_2 Leverage_{i,t} + \beta_3 ln(FA_{i,t} * WDL_{i,t} * WPB_{i,t}) + \varepsilon_{i,t} \quad (13)$$

$$CAR_{i,t} = \alpha_m + \sigma_t + \beta_1 ln(TA_{i,t}) + \beta_2 Leverage_{i,t} + \beta_3 \ln(Branches_{i,t}) + \varepsilon_{i,t} \quad (14)$$

where *TA* and *Leverage* control for bank *i*'s total assets and capital structure. I also control for bank type fixed effects α_m and time fixed effects σ_t. *t* = 1 (2) represents the *event period*

(the *event point*). *FA* is the fixed assets owned by a bank[49]; *WDL* is the weight of deposit-and-loan business among all types of business operated by that bank and is calculated as the ratio of interest revenues on total operating revenues; *WPB* is the weight of personal business in deposit-and-loan business and is calculated as the sum of personal deposits and personal loans over the sum of all types of deposits and loans; *Branches* is the number of physical branches currently run by a bank. I further take the natural log form of *TA*, *branches*, and the product of *FA*, *WDL*, and *WPB*. $\varepsilon_{i,t}$ is the error term.

Table 22 reports the results of potential heterogeneous reactions of banks. For banks with more fixed assets proportionally allocated to personal deposit-and-loan business, their stocks have exhibited larger-size positive responses to the events. Similarly, banks with more physical branches have greater positive CARs. The coefficients of explanatory variables of interest are positive and statistically significant in most cases. The coefficients of control variables show general consistency with the literature. Table 22 shows that banks with bigger total assets are less insensitive to the events, which is consistent with the study of Demsetz and Strahan (1997) and De Haan and Poghosyan (2012). Banks with higher leverage ratios are typically riskier and exhibit higher stock volatility, as higher leverage raises equity volatility for a given level of underlying asset volatility (e.g., see Stiroh, 2006; Agusman et al., 2008).

Table 22: The Reactions of Banks with Heterogeneous Stickiness to Field Operations

This table presents the results of regressions on panel data clustered by banks and events. The dependent variables are banks' short- and medium-term stock reactions. For brevity, I report representative CARs. Columns (1) and (2) show regression results on the short-term stock reactions (*CAR [–5, +5]*); Columns (3)–(6) show regression results on the medium-term stock reactions (*CAR [+1, +30]* and *CAR [+1, +90]*). Banks' stickiness to field operations is measured by *ln(FA*WDL*WPB)* and *Branches*, respectively. Some banks' fundamental attributes, bank size and capital structure, are controlled by *ln(TA)* and *Leverage*. I also control for the fixed effects of events

[49] I choose the absolute value of fixed assets rather than a percentage of total assets. Banks and lending marketplaces treat the credit they have channelled differently. While banks include their absorbed deposits and originated loans on their balance sheets, lending marketplaces do not. Since banks typically have an enormous size of deposits and loans, their fixed assets as a percentage of total assets are always negligible, which distort the measurement of the potential disadvantage against lending marketplaces.

and bank types, i.e., whether a bank is SOCBs, JSCBs, CCBs, or RCBs. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	CAR [–5, +5]		*CAR [+1, +30]*		*CAR [+1, +90]*	
	(1)	(2)	(3)	(4)	(5)	(6)
ln(TA)	–0.0872*	–0.0624	–0.0833*	–0.0616*	–0.0994*	–0.0523
	(0.0483)	(0.0422)	(0.0425)	(0.0333)	(0.0573)	(0.0331)
Leverage	0.3625	0.3309	0.4202**	0.4001*	0.6138**	0.5557**
	(0.2711)	(0.2660)	(0.1827)	(0.2235)	(0.2868)	(0.2685)
*ln(FA*WDL*WPB)*	0.1002*		0.1214*		0.1110**	
	(0.0552)		(0.0632)		(0.0476)	
Branches		0.0917		0.1123*		0.0723*
		(0.0624)		(0.0601)		(0.0371)
Bank Type Fixed Effects	Y	Y	Y	Y	Y	Y
Time Fixed Effects	Y	Y	Y	Y	Y	Y
No. of Obs.	104	104	104	104	104	104
R^2	0.1247	0.0936	0.2034	0.1862	0.2155	0.1753

5.4.2.2 Potential Disadvantage II: Higher Regulatory Burdens

The higher regulatory burdens on banks may induce additional costs and put their deposit-and-loan business at a disadvantage when competing with lending marketplaces (Buchak et al., 2018; Thakor, 2020; De Roure et al., 2022). Following Lee et al. (2013) and Fu et al. (2015), I use capital adequacy ratios and loan-to-deposit ratios to measure these regulatory burdens and collect necessary data from BankFocus. I propose two practical models below:

$$CAR_{i,t} = \alpha_m + \sigma_t + \beta_1 ln(TA_{i,t}) + \beta_2 Leverage_{i,t} + \beta_3 HighTier1Ratio_{i,t} + \varepsilon_{i,t} \quad (15)$$

$$CAR_{i,t} = \alpha_m + \sigma_t + \beta_1 ln(TA_{i,t}) + \beta_2 Leverage_{i,t} + \beta_3 HighLDR_{i,t} + \varepsilon_{i,t} \quad (16)$$

where *HighTier1Ratio* (*HighLDR*) equals one if a bank's tier 1 capital ratio (loan-to-deposit ratio) is no less than the median level among banks of the same type and equals zero otherwise.

Table 23 shows the reactions of banks with heterogeneous regulatory burdens. For banks of the same type, those with lower loan-to-deposit ratios show constantly higher positive

reactions in the short- and medium-term. By contrast, whether banks of the same type have higher or lower tier 1 capital ratios cannot effectively explain their stock reactions in the short term. A possible reason is that a bank's tier 1 capital ratio is a comprehensive indicator of its overall business, while its loan-to-deposit rate is more related to the deposit-and-loan business.

Table 23: The Reactions of Banks with Heterogeneous Regulatory Burdens

This table presents the results of regressions on panel data clustered by banks and events. The dependent variables are banks' short- and medium-term stock reactions. For brevity, I report representative CARs. Columns (1) and (2) show regression results on the short-term stock reactions (*CAR [–5, +5]*); Columns (3)–(6) show regression results on the medium-term stock reactions (*CAR [+1, +30]* and *CAR [+1, +90]*). Banks' regulatory burdens are measured by *HighTier1Ratio* and *HighLDR*, respectively. Some banks' fundamental attributes, bank size and capital structure, are controlled by *ln(TA)* and *Leverage*. I also control for the fixed effects of events and bank types, i.e., whether a bank is SOCBs, JSCBs, CCBs, or RCBs. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	CAR [–5, +5]		*CAR [+1, +30]*		*CAR [+1, +90]*	
	(1)	(2)	(3)	(4)	(5)	(6)
ln(TA)	–0.0864*	–0.0862*	–0.0833*	–0.0830*	–0.0890*	–0.0879*
	(0.0484)	(0.0447)	(0.0427)	(0.0432)	(0.0513)	(0.0505)
Leverage	0.3692	0.3378	0.4203**	0.4004*	0.6138**	0.5555**
	(0.2631)	(0.2610)	(0.1827)	(0.2234)	(0.2868)	(0.2684)
HighTier1Ratio	0.0104		–0.0315		0.0110*	
	(0.0090)		(0.0279)		(0.0064)	
HighLDR		–0.0732*		–0.0699*		–0.0743*
		(0.0433)		(0.0393)		(0.0408)
Bank Type Fixed Effects	Y	Y	Y	Y	Y	Y
Time Fixed Effects	Y	Y	Y	Y	Y	Y
No. of Obs.	104	104	104	104	104	104
R^2	0.1011	0.1235	0.1914	0.2022	0.2138	0.2140

5.4.2.3 Potential Disadvantage III: Insufficient Applications of FinTechs

Compared with lending marketplaces, banks may have fewer applications of FinTechs. On the one hand, lending procedures based on the internet, big data, and machine learning extend the financial inclusion of riskier borrowers (Philippon, 2020; Berg et al., 2020). By taking full advantage of soft information and digital footprints of borrowers, lending marketplaces have shown such extended financial inclusion is probably profitable and sustainable. On the other hand, robo-advising techniques significantly improve the user experience and decrease search costs for investors (Philippon, 2020). Thus, lending marketplaces with more applications of these technologies may reach a broader range of customers, some of whom are currently riskier than the minimum requirements of banks, while others are driven away

by less intelligent advisory services and lower rates of return from banks. The potential technological disadvantage may affect their future customer base as the loyalty of customers to services from lending marketplaces increases.

Following the work of Cheng and Qu (2020) and Wang et al. (2021), I construct FinTech indices of banks based on frequencies of FinTech-related keywords. A presumption is that listed banks are motivated to thoroughly convey their FinTech advantages through their reports and the media. Also, the intensity of press coverage should be a decent reflection of socioeconomic phenomena (Askitas and Zimmermann, 2009). I construct a dictionary of keywords with details shown in Appendix VII. For a robustness check, I also construct an additional supplementary measure of FinTech applications from the human resources perspective using data from CSMAR.

$$CAR_{i,t} = \alpha_m + \sigma_t + \beta_1 ln(TA_{i,t}) + \beta_2 leverage_{i,t} + \beta_3 ln(FAR_{i,t}) + \varepsilon_{i,t} \quad (17)$$

$$CAR_{i,t} = \alpha_m + \sigma_t + \beta_1 ln(TA_{i,t}) + \beta_2 leverage_{i,t} + \beta_3 ln(FNews_{i,t}) + \varepsilon_{i,t} \quad (18)$$

$$CAR_{i,t} = \alpha_m + \sigma_t + \beta_1 ln(TA_{i,t}) + \beta_2 leverage_{i,t} + \beta_3 ln(HRS_{i,t}) + \varepsilon_{i,t} \quad (19)$$

where *FAR* is the frequency of keywords from annual reports of listed banks. *FNEWS* is the frequency of keywords from targeted news articles using the Baidu search engine. *HRS* is the human resources structure of listed banks.

Table 24 shows the reactions of banks with different levels of FinTech applications. Except for the explanatory variables of interest, the model setup is the same as the previous heterogeneity tests. As illustrated, while control variables *ln(TA)* and *leverage* have shown patterns consistent with before, the status of FinTech applications among banks cannot explain their stock reactions. The insignificance implies that lending marketplaces may not have built technical barriers before being interrupted by the policy. Therefore, the market does not think FinTechs adopted by lending marketplaces can ever be a severe threat to banks

in the future, which is likely to be the case as banks dominate the financial system of China, own much more capital for R&D, and are more competitive than lending marketplaces in attracting FinTech engineers.

Table 24: The Reactions of Banks with Heterogeneous Applications of FinTechs

This table presents the results of regressions on panel data clustered by banks and events. The dependent variables are banks' short-and medium-term stock reactions. For brevity, I report representative CARs. Columns (1)–(3) show regression results on the short-term stock reactions (*CAR [–5, +5]*); Columns (3)–(9) show regression results on the medium-term stock reactions (*CAR [+1, +30]* and *CAR [+1, +90]*). Banks' applications of FinTechs are measured by *ln(WFAR)*, *ln(WFN)*, and *HRS*, respectively. Banks' fundamental attributes, bank size and capital structure, are controlled by *ln(TA)* and *Leverage*. I also control for the fixed effects of events and bank types, i.e., whether a bank is SOCBs, JSCBs, CCBs, or RCBs. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	CAR [–5, +5]			*CAR [+1, +30]*			*CAR [+1, +90]*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ln(TA)	–0.0833*	–0.0794*	–0.0794*	–0.0812*	–0.0812*	–0.0811*	–0.0844*	–0.0823*	–0.0823*
	(0.0448)	(0.0436)	(0.0436)	(0.0439)	(0.0438)	(0.0438)	(0.0440)	(0.0433)	(0.0433)
Leverage	0.3717	0.3502	0.3500	0.4212*	0.4209*	0.4210*	0.6003*	0.6007*	0.6006*
	(0.2413)	(0.2304)	(0.2304)	(0.2353)	(0.2349)	(0.22351)	(0.3127)	(0.3112)	(0.3112)
ln(WFAR)	0.0510			0.0411			0.0402		
	(0.0415)			(0.0337)			(0.0356)		
ln(WFN)		–0.0312			–0.0325			–0.0327	
		(0.0188)			(0.0208)			(0.0210)	
HRS			–0.2223			–0.2214			–0.2208
			(0.1416)			(0.1428)			(0.1428)
Bank Type Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
No. of Obs.	104	104	104	104	104	104	104	104	104
R^2	0.0723	0.0711	0.0711	0.1818	0.1822	0.1823	0.1977	0.1967	0.1967

5.5 Chapter Conclusion and Policy Implications

This chapter examines the external wealth effects of severe interventions of governments against the marketplace lending industry in China. Using stock data, I find listed banks as traditional incumbents of China's credit market react positively to these exogenous interventions against their competitors. By contrast, listed nonbank financial institutions do not show significantly positive reactions in most model settings. After systematically checking the related regulatory documents, I find the regulatory environment of financial institutions during the studied periods remains qualitatively stable, possibly leaving no alternative explanations for the divergent performance of banks and nonbank financial institutions. The positive reactions of the banks are consistent with the view that the competition from the marketplace lending industry outweighs the synergies that the industry brings. Heterogeneity tests provide more details about the heterogeneous reactions of banks and reveal their potential disadvantages when competing with lending marketplaces. Banks with more fixed assets proportionally allocated to serve personal deposit-and-loan business and with more physical branches have positive reactions of greater size. Similarly, banks with higher regulatory costs have greater positive reactions. However, the reactions of their stocks are insensitive to their conveyed applications of financial technologies (FinTechs) and their structure of human resources, implying that banks do not face technical barriers when competing with lending marketplaces. Instead, the real disadvantages are likely to be their adherence to field operations and their regulatory burdens.

The systematic review of regulation documents reveals a mismatch between the development of China's marketplace lending industry and its supervision framework, which largely leads to its vulnerability, fraudulence, and subsequent failure of substantial size. As various forms of FinTechs and FinTech organisations continue emerging, a lesson that should be learnt through the case of lending marketplaces is the necessity of the early establishment of tailored and preventative regulation frames. As for banks, this chapter studies their stock

data and has results implying that their dominance in the credit market has been challenged. Brutal halts of the business of competitors by governments mean that banks can be immediately relieved of the intensive competition. Although my results show banks can enjoy some short-term wealth benefits, they may be less motivated to keep refining their business models and adopting FinTechs in the long term, which necessitates competition from other forms of well-supervised FinTech organisations.

6. Conclusions and Policy Suggestions

This thesis studies the nexus between commercial banks and lending marketplaces in China through multiple dimensions. The dominant role of banks in China's financial system means their influence on lending marketplaces, and arguably other FinTech institutions, is prominent. Their influence on lending marketplaces has become my major discussion. This thesis shows the underperformance of commercial banks is an external reason for the popularity of China's lending marketplaces. Such underperformance includes i) the limited financial inclusion of individuals, households, and small businesses induced by insufficient inter-bank competition and ii) the dysfunction in providing the real economy with sufficient credit during a crisis. The thesis also shows that bank stocks react to their marketplace lending competitors. Bank stocks enjoy positive wealth effects from the government's cracking down on lending marketplaces, consistent with the view that the uninterrupted development of lending marketplaces can be a net threat to the future of banks. Overall, my research recognises the contribution of lending marketplaces, a popular type of FinTech institution, to enriching the diversity and enhancing the functionality of China's credit market, despite the lack of authoritative supervision that led to misconduct during its development.

Specifically, I first examines how China's regional banking market competition influences the use of credit from lending marketplaces. Using loan-level data from a leading marketplace in China and data on bank branches, I show that regional banking market competition affects the creditworthiness of marketplace borrowers. All else being equal, marketplace borrowers from concentrated banking markets are more likely to be creditworthy than marketplace borrowers from competitive banking markets. Heterogeneity tests show that the association between banking market competition and the creditworthiness of marketplace borrowers is particularly strong when (i) entrants (new banks) contribute more competition to the banking markets; (ii) borrowers are younger; and (iii) borrowers are new to the marketplace. The main empirical results are robust and continue to hold after accounting for

potential endogeneity. The empirical results suggest borrowers migrate from the banking sector to the lending marketplace when the banking market is concentrated, and banking competition improves the level of financial inclusion of individuals and households through relaxed credit checks. My results are also consistent with the presence of information asymmetry and information dispersion among the banks.

I then conduct a case study to investigate the performance of China's lending marketplaces in supporting individuals, households, and small business during the pandemic, COVID-19. Using the same proprietary dataset from the leading marketplace, I find that the pandemic's impact was a mixture of two effects. First, the pandemic had a direct impact on pre-existing marketplace borrowers. The borrowing activities of these pre-existing borrowers were inhibited by the pandemic. They tended to borrow more small-sized and short-term loans than the ex-ante level, and the change in their preference significantly altered the ex-ante distribution of loan sizes and loan maturities. Second, the pandemic also indirectly influenced the marketplace lending industry through marketplace newcomers from banks. Some bank-dependent borrowers could not be served by banks due to lockdowns and mobility restrictions; at least some of them were diverted away by marketplaces. The contribution of these marketplace newcomers was enormous, significantly increasing the total credit volume through a marketplace. Large-sized and long-term marketplace loans made during the outbreak of the pandemic in China were mainly contributed by these newcomers.

To explore the impacts of lending marketplaces on banks, I examine the external wealth effects of severe interventions by governments against the marketplace lending industry in China. Using stock data, I find listed banks as traditional incumbents of China's credit market react positively to these exogenous interventions against their competitors. Their positive reactions are consistent with the view that the competition from the marketplace lending industry outweighs the synergies that the industry brings. Heterogeneity tests provide more details about their heterogeneous reactions and reveal potential disadvantages of banks when

competing with lending marketplaces. Those with more fixed assets proportionally allocated to serve personal deposit-and-loan business and with more physical branches have positive reactions of greater size. Similarly, banks with higher regulatory costs have greater positive reactions. However, the reactions of their stocks are insensitive to their conveyed applications of financial technologies (FinTechs) and their structure of human resources, implying that banks do not face technical barriers when competing with lending marketplaces. Instead, real disadvantages are likely to be adherence to field operations and regulatory burdens.

This thesis generates comprehensive policy suggestions. I first recognise the necessity of inter-bank competition given their dominance in China's credit market. The government should not only advocate for greater banking competition but also encourage and help non-state commercial banks to gain higher market shares, which is potentially a more effective way to improve the financial inclusion of individuals, households, and small businesses. Considering the preference of China's borrowers for bank loans, the government should leave riskier borrowers with access to credit based on the premise of controllable risks, such as through lending marketplaces, (online) micro-loan companies, or other types of FinTech credit intermediaries. Next, it is crucial for commercial banks to extend the application of FinTechs and develop more online options for borrowers, which have been indicated as more efficient and functional during a crisis. Finally, the government should fully realise that introducing new forms of credit institutions to enhance the overall credit market competition is a double-edged sword. On the one hand, banks may be less motivated to keep refining their business models and adopting FinTechs in the long term due to the lack of competition from FinTech firms. On the other hand, aggressive entry of poorly supervised FinTech firms largely leads to their vulnerability, fraudulence, the subsequent failure of substantial size, and eventual social instability. A lesson that should be learnt through the case of lending marketplaces is the necessity of the early establishment of well-tailored and preventative regulation frameworks.

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Appendix I: Estimates of the Size of China's Shadow Banking Sector[50]

Sources	Estimation Periods	CNY (trillion)	USD (trillion)	% of GDP	Description of Components
Lu et al. (2015)	Dec 2012	27	4.33 (S(CNY/USD) =6.2348)	50.14% (GDP=53.85 trillion)	Four types of shadow banking are included. They are i) nonbanking credits generated in formal financial institutions, ii) other off-balance-sheet activities within the banking system, iii) nonbanking credits generated by informal financial systems and the real economy, and iv) credit guarantees.
Yi (2013)	Jan 2013	30	4.82 (S(CNY/USD) =6.2195)	55.71% (GDP= 53.85 trillion)[51]	Shadow banking includes entities such as hedge funds, private equity funds, money market funds, bond insurers, and structured investment vehicles. It also includes nonbank financial institutions like trusts, microfinance companies, and wealth management firms.
Elliott et al. (2015)	Dec 2013	25	4.13 (S(CNY/USD) =6.0518)	42.16% (GDP= 59.30 trillion)	Shadow banking is financial institutions with functions and risks similar to banks. Components include institutions issuing entrusted loans, trust loans, bankers' acceptances, and micro loans, as well as entities conducting interbank entrusted loan payments and financial leasing.
Sheng et al. (2015)	Dec 2015	32.2	4.94 (S(CNY/USD) =6.4812)	46.74% (GDP= 68.89 trillion)	N/A

[50] Some results are my calculations based on given data from sources. Some documents only provide CNY (USD) estimates of the aggregate scale of shadow banking in China. In such cases, I use the CNY/USD close prices from the last trading day of corresponding months to calculate USD (CNY) estimates. For documents that provide CNY and USD estimates, I keep the CNY estimates only and calculate the USD estimates to maintain the consistency of statistical calibre. The CNY/USD exchange rates are from Yahoo Finance. The data of China's historical GDPs are obtained from National Bureau of Statistics of China. For details of CNY/USD exchange rates, see:

https://finance.yahoo.com/quote/USDCNY%3DX/history?period1=991267200&period2=1582588800&interval=1d&filter=history&frequency=1d

For details of China's historical GDPs, see: http://data.stats.gov.cn/easyquery.htm?cn=C01

[51] I use the GDP of 2013 instead of 2014 for a better estimate of the relative size of shadow baking at the beginning of 2014.

Table continued...

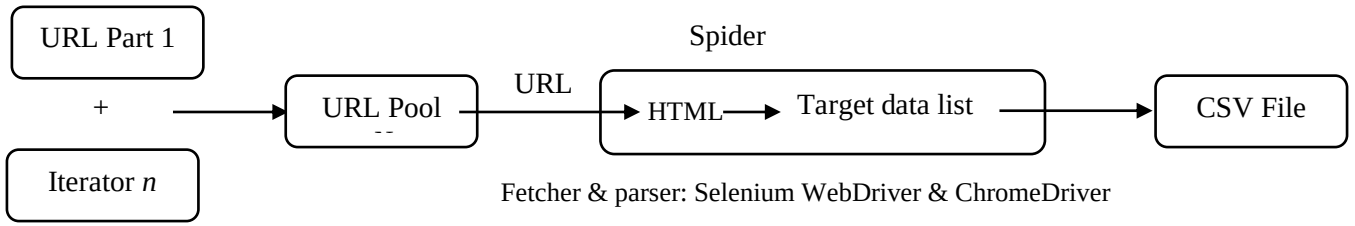
Sources	Estimation Periods	CNY (trillion)	USD (trillion)	% of GDP	Description of Components
Ehlers et al. (2018)	Dec 2016	23.7 – 57.3[52]	3.41 – 8.25 (S(CNY/USD) =6.9453)	31.75% - 76.77% (GDP= 74.64 trillion)	The components include all financial instruments that fulfil functions of credit intermediation like banks without the burden of heavy banking regulation.
FSB (2018)	Dec 2016	48.62	7 (S(CNY/USD) =6.9453)	65.14% (GDP= 74.64 trillion)	The narrow measure of shadow banking includes nonbank financial entities involving in credit intermediation that may pose financial stability risks.
Sun (2019)	Dec 2018	72.47	10.54 (S(CNY/USD) =6.8772)	78.83% (GDP= 91.93 trillion)	Chinese shadow banking is classified into two types: bank's shadow and traditional shadow banking. Bank's shadow is "bank activities that provide funding for enterprises through the creation of credit money, but which circumvent regulatory restrictions and constraints on lending by adopting non-standard accounting measures". Traditional shadow banking refers to "credit creation activities undertaken by nonbank financial institutions".
FSB (2020)	Dec 2018	53.64	7.8 (S(CNY/USD) =6.8772)	58.35% (GDP= 91.93 trillion)	The narrow measure of "nonbank financial intermediation"[53] is comprised of nonbank financial institutions involving in credit intermediation activities that may pose bank-like financial stability risks and/or regulatory arbitrage.

[52] Ehlers et al. (2018) offer three methods to calculate the shadow banking size. These methods are based on different stages of credit intermediation. Sizes measured at the "ultimate creditor stage" and "intermediate stage" are 57.3 trillion and 37.1 trillion respectively. The size measured at the "ultimate borrower stage" is 23.7 trillion if WMPs and trust investments in bond markets excluded and is 40.8 trillion if these products included.

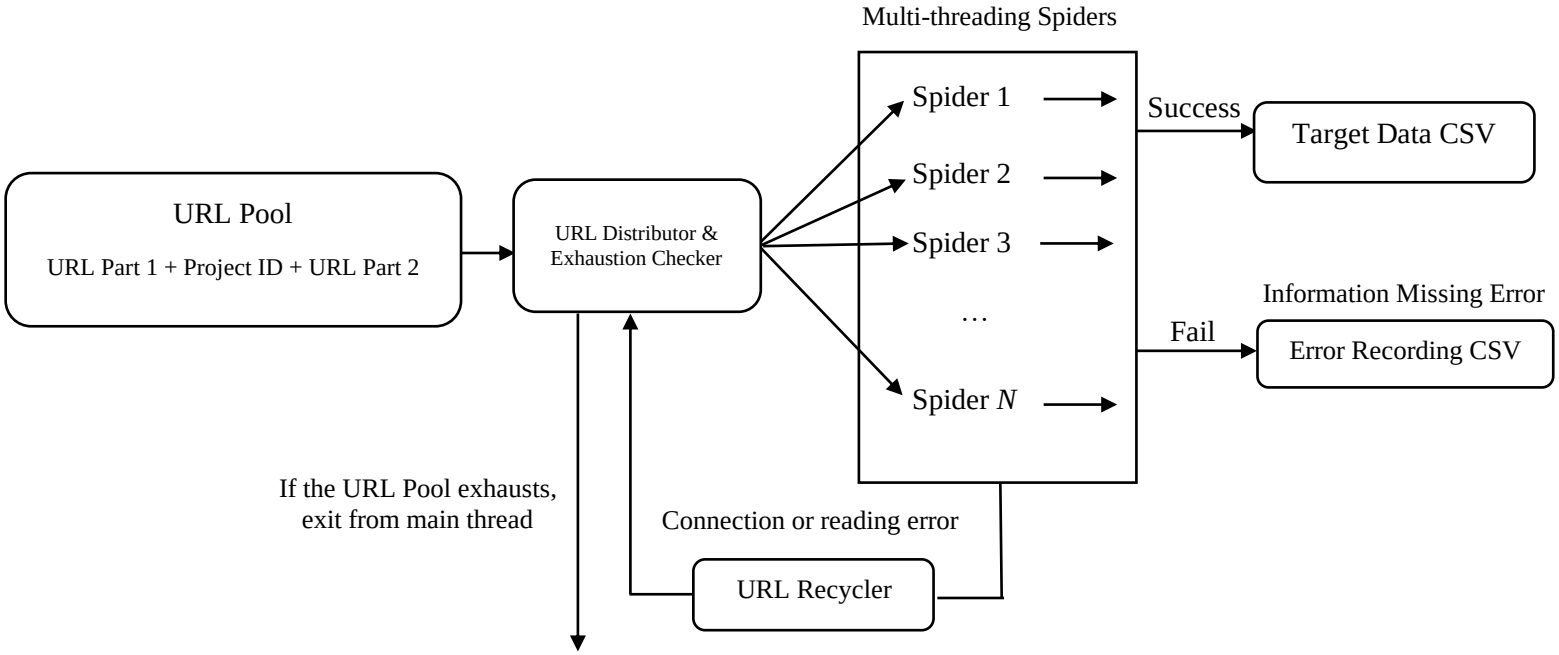
[53] The FSB decides to replace the term "shadow banking" with "nonbank financial intermediation" to facilitate future monitoring. This change does not affect the economic essence and the coverage of the original term.

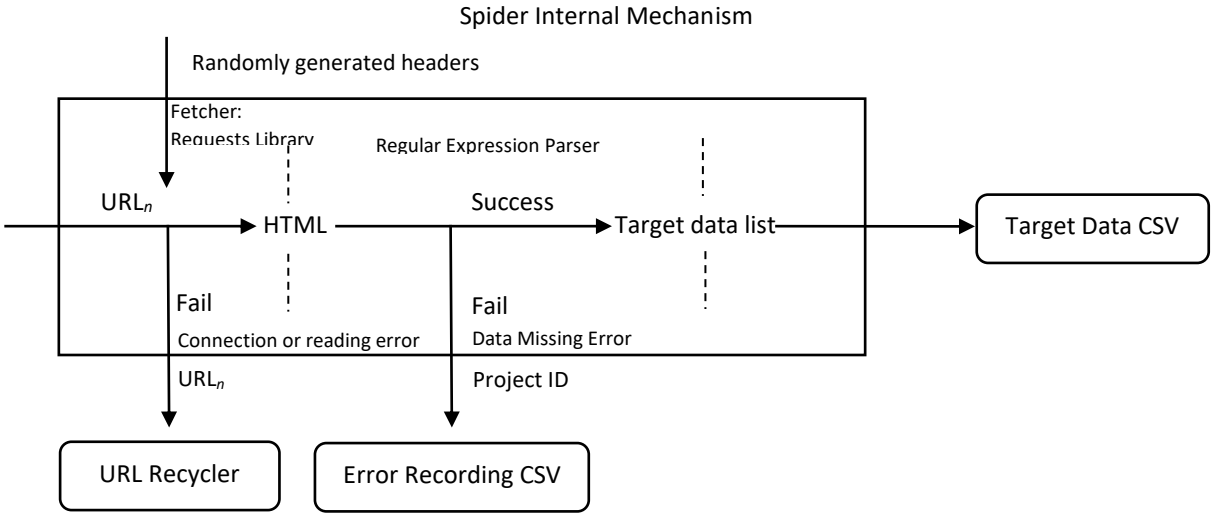
Appendix II: The Structures of Web Spiders

Appendix II.1 The Structure of Web Spiders Collecting the Platforms Information from NIFA

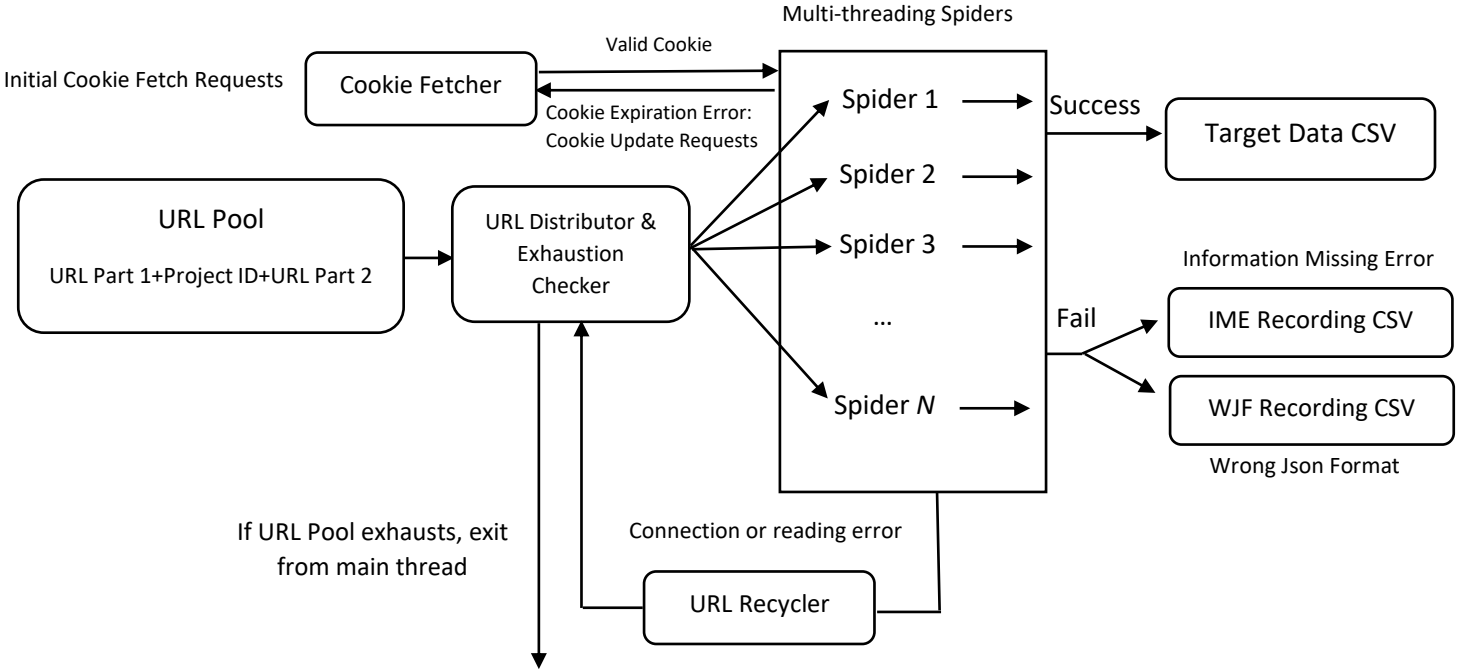


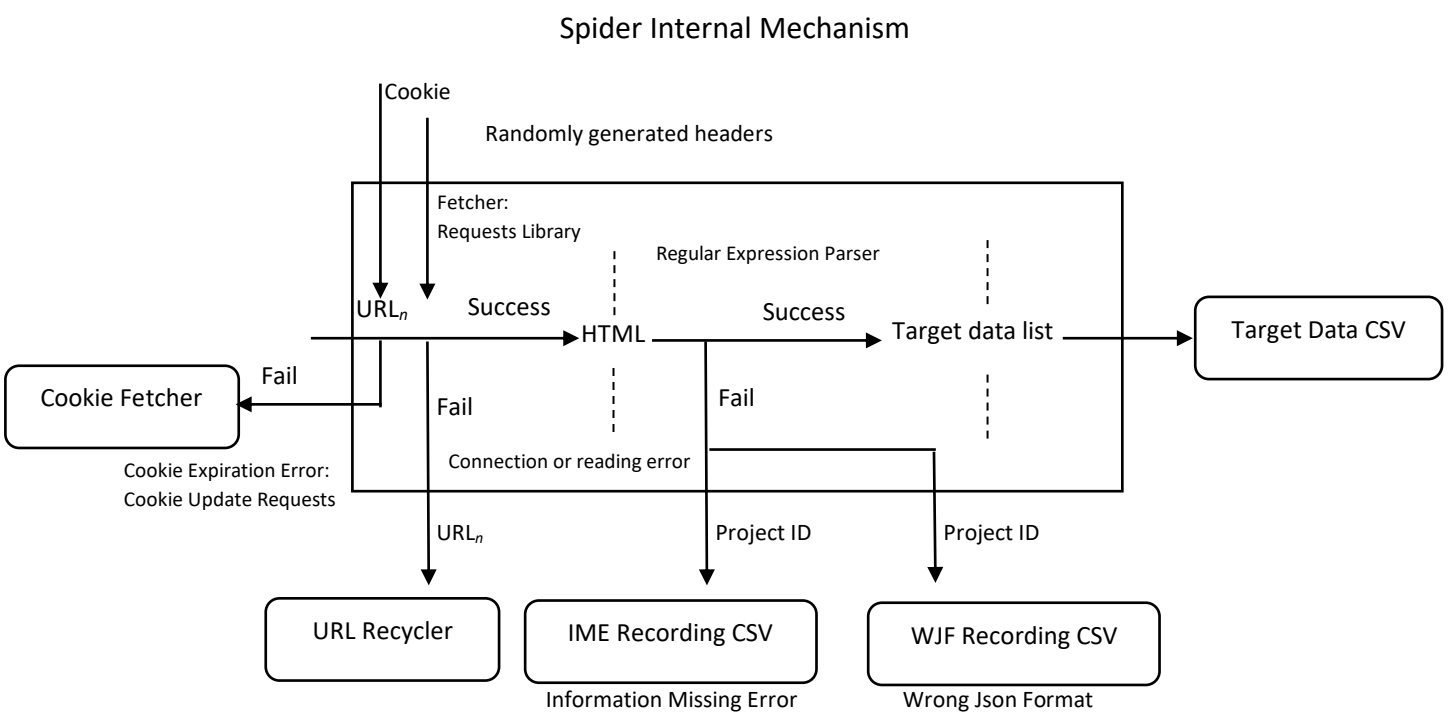
Appendix II.2 The Structure of Web Spiders Collecting the Projects Information from NIFA





Appendix II.3 The Structure of Web Spiders Collecting the projects from RRD Commercial Website





I can publish the detailed codes on GitHub after publishing the study upon request.

Appendix III: Chapter 3 — Variable Definitions and Data Sources

Variable Name	Definition	Data Source
Panel A. Loan Application Characteristics		
Success	A dummy variable that equals 1 if an application is fully funded, and 0 otherwise.	RRD
Fraction	Proportion of bid amount out of the total amount requested by the borrower.	RRD
Amount	Requested loan amount in 10,000 RMB.	RRD/YLD
Maturity	Loan maturity in months.	RRD/YLD
Spread	The risk premium in percentage of a loan over the benchmark lending rate.	RRD/YLD
Words	The length of the application statement from the borrower.	RRD
Bidders	The number of bidders for a loan.	RRD
Overdue	The number of times a borrower is overdue in the monthly instalments of principal and interest.	RRD/YLD
SuccessTimes	The number of times a borrower has successfully borrowed from the marketplace before.	YLD
RepaidTimes	The number of times a borrower has repaid the instalments on time before.	YLD
Default	A dummy variable that equals 1 if the creditors are repaid by the platform in the end, and 0 otherwise.	RRD
Panel B. Borrower's Demographic Characteristics		
Age	The age of a borrower.	RRD/YLD
Young	A dummy variable that equals 1 if the borrower is less than 30 years old, and 0 otherwise.	RRD
Gender	A dummy variable that equals 1 if the borrower is female, and 0 otherwise.	RRD/YLD
Education	It is an integer variable ranging from 1 to 4. It equals 1 if the borrower's highest qualification is secondary or below, 2 if the borrower's highest qualification is post-tertiary, 3 if the borrower's highest qualification is a bachelor's degree, and 4 if the borrower's highest qualification is a master's degree or above.	RRD/YLD
High Edu.	A dummy variable that equals 1 if *Education* >= 3, and 0 otherwise.	RRD/YLD
Marriage	A dummy variable that equals 1 if the borrower is married, and 0 otherwise.	RRD/YLD
Income	It is an integer variable ranging from 1 to 6 based on the monthly income reported by the borrower during application. It equals 1 to 6 if the monthly income falls within the following ranges: 0–999, 1000–4999, 5000–9999, 10000–19999, 20000–49999, >=50000 RMB.	RRD/YLD
High Inc.	A dummy variable that equals 1 if *Income*>= 4, and 0 otherwise.	RRD/YLD
Work Exp.	An integer variable indicating employment length in years. Possible values vary from 1 to 4 if the employment length falls within the following ranges: 0–1, 2–3, 4–5, >5 years.	RRD/YLD

Variable Name	Definition	Data Source
High Exp.	A dummy variable that equals 1 if *Work Exp.*>= 3, and 0 otherwise.	RRD/YLD
House	A dummy variable that equals 1 if the borrower has a house, and 0 otherwise.	RRD/YLD
Home Loan	A dummy variable that equals 1 if the borrower has a home loan, and 0 otherwise.	RRD/YLD
ApplicationNum	Number of applications a borrower has listed on RRD before.	RRD
Panel C. Provincial Competition Indices		
HHI	Herfindahl-Hirschman Index of the local banking market competition in terms of bank branches.	Bank Websites, CBIRC, and Tianyancha
HHIEZ	The average Herfindahl-Hirschman Index of other provinces in the same economic zone.	
K	The number of bank brands in the province.	
CRn	Concentration ratio for *n* largest banks in the local banking market in terms of bank branches.	
MSJSCB	The market share of JSCBs in terms of bank branches.	
MSCCB	The market share of CCBs in terms of bank branches.	
TACR4	The concentration ratio of the four largest banks in terms of total assets.	Provincial Finance Yearbooks, PBS, PBC
TDCR4	The concentration ratio of the four largest banks in terms of total deposits.	
TLCR4	The concentration ratio of the four largest banks in terms of total loans.	
TASOCB	The market share of SOCBs in terms of total assets.	
TDSOCB	The market share of SOCBs in terms of total deposits.	
TLSOCB	The market share of SOCBs in terms of total loans.	
Panel D. Provincial Control Variable and Provincial Application Volume		
Population	Number of permanent residents in a province per 10,000 people.	NBS
GDP	Gross Domestic Product of a province in 100 million RMB.	NBS
FinDev	Ratio of total new loans originated by financial institutions to provincial GDP.	PBC and NBS
GDP per capita	Quarterly GDP per capita in 1,000 RMB.	NBS
PTB	Number of total marketplace applicants in a province per 1,000 people.	RRD
PTLN	Number of total marketplace applications in a province per 1,000 records.	RRD
PTLA	Total amount of money requested by all applications in a province in 100 million RMB.	RRD
Panel E. DID Analysis		
Henan	A dummy variable that equals 1 if a borrower comes from Henan Province, and 0 otherwise.	RRD
Gansu	A dummy variable that equals 1 if a borrower comes from Gansu Province, and 0 otherwise.	RRD

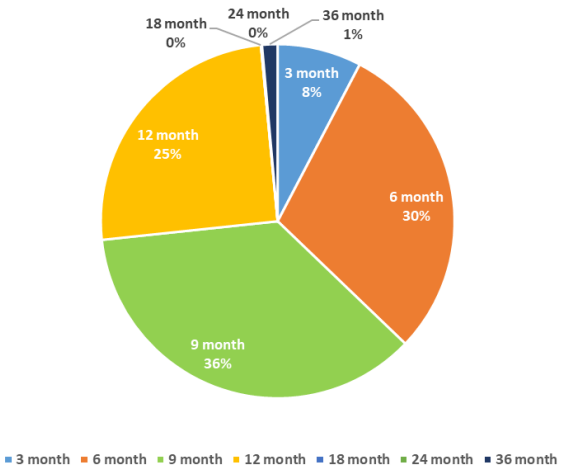
Variable Name	Definition	Data Source
Post 1	A dummy variable that equals 1 if an application is listed after the establishment of Zhongyuan Bank, and 0 otherwise.	RRD
Post 2	A dummy variable that equals 1 if an application is listed after the establishment of Bank of Gansu, and 0 otherwise.	RRD

Appendix IV: Summary Statistics of Chapter 4

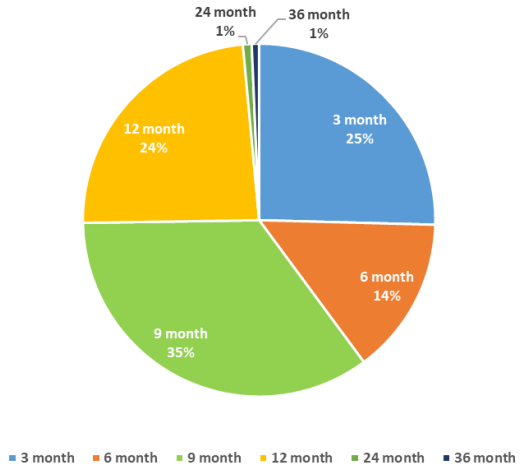
IV.1 The Proportion of P2P Loans with Various Maturities in RRD

(Pre- vs. post-pandemic)

Panel A: Pre-pandemic (2019Q3 & 2019Q4)



Panel B: Post-pandemic (2020Q1 & 2020Q2)



IV.2 Summary Statistics of P2P platforms

(N = 78)

	Min.	Mean	Max.	S.D.	C.V.
Accumulative borrowing amount (CNY 10,000)	28,160	5,084,024.85	39,416,143	8,211,600.65	161.52
Accumulative number of loans	369	5,099,916.76	61,404,064	10,877,959.40	213.30
Accumulative number of borrowers	138	1,775,497.81	16,533,709	3,137,593.43	176.72
Accumulative number of lenders	1,187	469,710.14	392,7610	803,856.25	171.14

These data reflect the operational situation of P2P platforms by the date 31/01/2020.

IV.3 Summary Statistics of Loan Information Extracted from RRD and NIFA
(2010Q4 – 2020Q2)

Variable	Min.	Mean	Median	Mode	Max.	S.D.	*N*
Panel A: All Applications							
Amount	250	17851.30	2650	500	990000	42307.79	8034610
Maturity	1	12.16	9	9	48	9.70	8034610
APR[54]	3%	10.78%	10.2%	10.2%	24.4%	1.32%	8034610
Credit Scores	0	167.29	180	180	245	44.23	7630760
Panel B: Failed Applications							
Amount	1000	59918.79	30000	50000	990000	90823.63	579511
Maturity	1	15.87	12	24	48	9.21	579511
APR	3%	13.37%	13%	13%	24.4%	2.88%	579511
Credit Scores	0	15.78	20	20	245	24.70	579502
Panel C: Funded Applications							
Amount	250	14581.25	2100	500	950000	33758.18	7455099
Maturity	1	11.87	9	9	48	9.69	7455099
APR	3%	10.58%	10.2%	10.2%	24.4%	0.83%	7455099
Credit Scores	0	179.74	180	180	245	5.03	7051258

Table IV.3 here summarises the descriptive statistics of loan information extracted from RRD and NIFA from 2010Q4 to 2020Q2. As shown, most observations in the data set are funded applications. However, the proportion of funded applications to the total applications shown in the crawled dataset is somewhat meaningless because, after 2016, RRD tends to stop publishing information about failed applications. Thus, this ratio does not reflect the actual failure rate of applications. Moreover, the Pandemic broke out at the beginning of 2020, which means all P2P loans published during our focus period are funded applications. As a result, our focus moves to the funded applications.

[54] APR is the abbreviation of annual percentage rate of interest.

IV.4 Summary statistics of the time used from the bid issuance to full fundraising of loan projects
(Pre- vs. post-pandemic)

	Min.	Mean	Median	Mode	Max.	S.D.	*N*
2019 Q3	0	15.90	0	0	194825	761.71	1,155,730
2019 Q4	0	9.82	1	0	146600	358.50	1,762,205
2020 Q1	0	16.44	0	0	43834	498.82	1,522,014
2020 Q2	0	6.32	0	0	350176	781.93	2,191,511

Table IV.4 here summarises the descriptive statistics of the time in seconds used from the bid issuance to full fundraising of loan projects during the pre- and post-pandemic periods. The statistics indicate that there were many projects instantly funded in full amounts once they were published. The reason is that RRD started to strongly suggest investors buy shares of funds developed by RRD and let the funds invest large quantities of loan projects on the platform. Renrendai said this mechanism could effectively diversify the risk raised from directly investing in a loan project. These funds developed by RRD will compete with solo investors in investing loan projects, causing small-size projects to be fully funded instantly.

Appendix V: Chapter 4 — Summary of Variables

Variable Name	Explanation
	Panel 1 Summary of dependent variables
The Loan Volume	Money amounts of funded loans & Number of funded loans
Distribution of loan sizes	Average and quantiles of the loan size distribution
Distribution of loan maturities	Average and quantiles of the loan maturity distribution
	Panel 2 Summary of explanatory variables of interest
$Pandemic1_{c,t}$	A quarter dummy variable indicating whether a record of city c is gathered at 2020Q1.
$Pandemic2_{c,t}$	A quarter dummy variable indicating whether a record of city c is gathered at 2020Q12.
$Wuhan_{c,t}$	A city dummy variable that distinguishes city Wuhan from other cities.
$Hubei_{c,t}$	A city dummy variable that distinguishes cities of Hubei (Wuhan not included) from other cities.
$CapitalCircle_{c,t}$	A city dummy variable that distinguishes Beijing, Tianjin, and cities of Hebei from other cities.
	Panel 3 Summary of control variables
$GDP_{c,t}$[55]	The GDP per capita of city c at time t. It is calculated as the GDP of city c at time t divided by the permanent resident population of city c at time t.
$FirstIndustry_{c,t}$[56]	It is the weight of output value of enterprises in the first industry[57] in the city 's total GDP at time t.
$SecondIndustry_{c,t}$	It is the weight of output value of enterprises in the second industry in the city 's total GDP at time t.
$Unemployment_{c,t}$	The unemployment rate of residents of city c at time t, it is number of registered unemployed persons divided by permanent resident population.

[55] I manually collect GDP data of cities and permanent resident population data from statistical yearbooks of provinces.

[56] This variable and the following control variables are all manually collected from CEInet Statistics Database.

[57] According to the government document "Industry Classification of National Economy", enterprises engaging in agriculture, forestry, animal husbandry, and fishery belong to the first industry; enterprises engaging in mining, manufacturing, electricity, heat, gas and water production and supply, and construction belong to the second industry, enterprises engaging in service belong to the third industry. To avoid perfect multicollinearity, only two variables representing the weights of the first and second industries are involved.

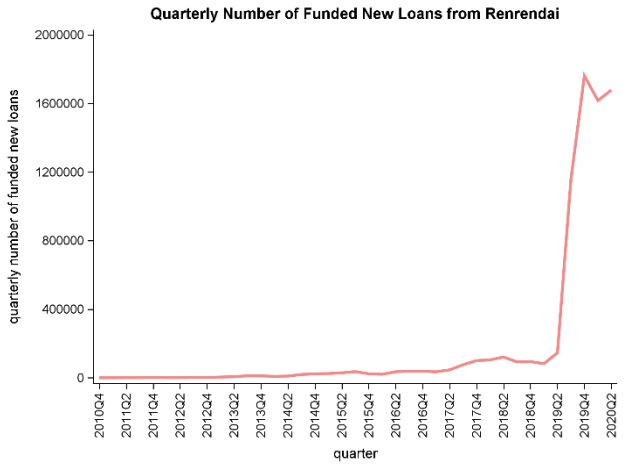
Variable Name	Variable Explanation
$Deposits_{c,t}$	The personal deposits per capital. It is calculated as the personal savings balance of city c at time t divided by permanent resident population of city c at time t.
$Loans_{c,t}$	The loans per capita. It is calculated as the originated loans balance of city c at time t divided by permanent resident population of city c at time t.
$HHI_{c,t}$[58]	The Herfindahl − Hirschman Index $= \sum_{b=1}^{b_c}(\#branch_b / \sum_{b=1}^{b_c} \#branch_b)^2 \times 10000$, where b_c is the total number of bank brands in city c at time t.
$CR6_{c,t}$	The Concentration Ratio for Six largest banks $= \sum_{n=1}^{6} \#branch_n / \sum_{b=1}^{b_c} \#branch_b$, $n = 1, \dots, 6$ are the six largest banks by total assets of the whole bank and number of branches.[59]
	Panel 4 Summary of time structure variables
$LevelShift_t$	An indicator variable to show whether certain major level shift occurs in the long term trends. The detailed explanation is in Appendix VI.
$FirstQuarter_t$	An indicator variable to show whether the current quarter is the first quarter of a year.
$SecondQuarter_t$	An indicator variable to show whether the current quarter is the second quarter of a year.
$ThirdQuarter_t$	An indicator variable to show whether the current quarter is the third quarter of a year.

[58] I manually collect data of cities' bank branches from TianYanCha.com, the most comprehensive database specialised in gathering and disclosing business information of mainland companies. However, it is inaccessible for IP addresses outside China mainland. These data are used to calculate the Herfindahl-Hirschman index and the concentration ratio.

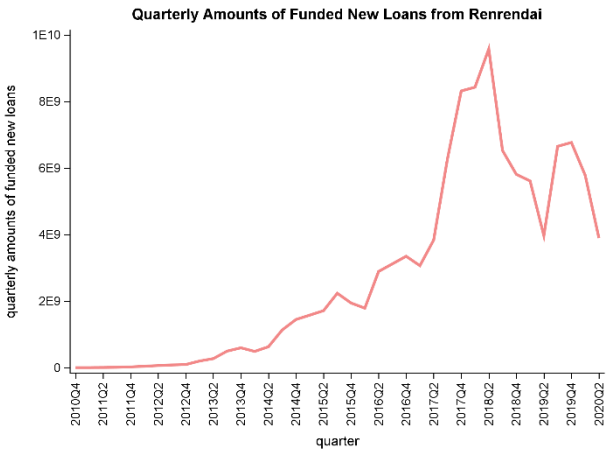
[59] In most cities, the six largest banks in terms of total assets of the whole bank and number of branches are the six state-owned commercial banks (SOBs). They are Industrial and Commercial Bank of China (ICBC), Agricultural Bank of China (ABC), Bank of China (BOC), China Construction Bank (CCB), Bank of Communications (BOCOM), and Postal Savings Bank of China (PSBC). So the concentration ratio of the largest six banks essentially equals the market share of state-owned commercial banks in city c at time t.

Appendix VI: Long-term Trends of Funded New Loans from RRD

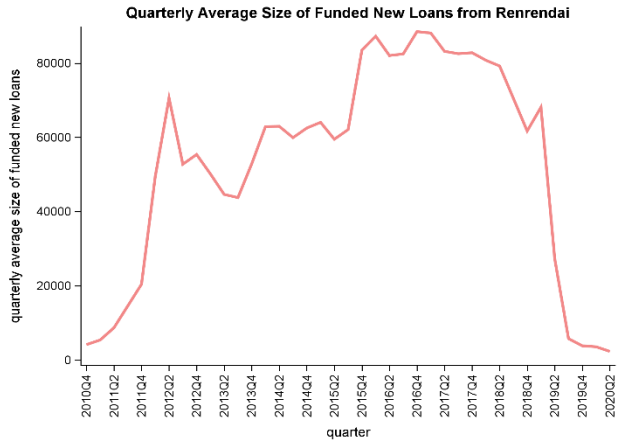
Panel 1



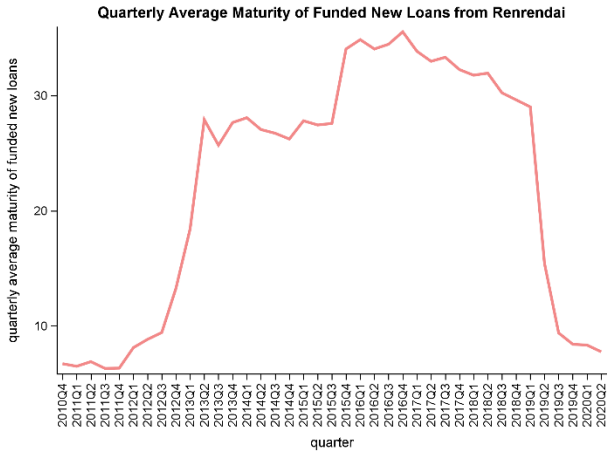
Panel 2



Panel 3



Panel 4



A noticeable feature of these trends is significant level shifts. For example, there was a massive boom in the number of new funded loans after the 2nd quarter of 2019. Since this level shift occurred before outbreak of the Pandemic, I use a dummy variable, *LevelShift*, to control for its impact to the model fitting. However, this explosion of new loan numbers was not followed by a matched increase in new loan amounts. So, a panel-data regression model when the dependent variable is cumulative amounts of new loans should not include *LevelShift*, that is why this variable is an optional variable.

Significant level shifts also occurred in terms of average loan size at around 2011Q4 and 2019Q3, and in terms of average loan maturity at around 2012Q4 and 2019Q3. Nevertheless, I still try to use a systematic method to set the dummy variable, rather than based on the pre-set in mind. So I have run the panel-data regression model 38 times over each dependent variable; each time I set a dummy variable to indicate one of the 38 quarters. I find that the dummy variable is statistically significant only when it indicates the 2nd quarter of 2019 if the dependent variable is the number of funded new loans, and only when it indicates the 3rd quarter of 2019 if the dependent variable is the average size or the average maturity of funded new loans. The reason is that I have included year fixed effects; thus, any further application of quarter dummies indicating the beginning or end of a year, the 4th quarter of 2011 or the 4th quarter of 2012 in our case, will cause multicollinearity.

Appendix VII: The Dictionary of FinTech-related Keywords and Other Construction Details

I classify banks' FinTechs into three main categories: Internet Technology, Data Science, and Artificial Intelligence. I summarise the text information from listed banks' annual reports and news and establish initial keywords under these three categories, effectively reflecting banks' overall applications of FinTechs. To construct *FAR*, I calculate the keyword frequency in listed banks' annual reports at the bank-year level. To construct *FNEWS*, I first initiate every search on Baidu by constructing a request constituted of four parts: i) a listed bank's name, ii) year, iii) one of the following keywords, iv) one of the top ten most commonly used Chinese idioms.[60] After identifying the target articles, I then calculate the keyword frequency in these target articles at the bank-year level.

Dimensions	Internet Technology	Data Science	Artificial Intelligence
Keywords	Internet	Big Data	Machine Learning
	Network	Data Analysis	Deep Learning
	Online	Data Technology	Robo-advising
	Mobile	Dataset	Face Recognition
	Cloud Technology	Data Layer	
	Cloud Computing		
	Cloud Finance		

[60] A challenge for identifying target articles is that after several pages of search results, Baidu starts showing articles with low relevance. Following the research by Hou et al. (2016), I find that an effective way to narrow down the results is to combine the search request with one of the top ten commonly used Chinese idioms from the "Language Situation Report in China" issued by the Ministry of Education of PBC.