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In the Shadow of Big Tech Lending

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JEL classification: G21, G28, G51

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1 Introduction

The rise of financial technology (FinTech) has changed the landscape of the financial industry, disrupting traditional ways of providing financial services (Goldstein et al., 2019). One important group of major FinTech players are large technology companies, dubbed as "Big Techs", with their credit businesses estimated to exceed one trillion dollars in 2023 (Cornelli et al., 2020). A burgeoning literature has shown the benefits of FinTech lending and Big Tech credit in helping underprivileged borrowers to overcome borrowing constraints and thus promoting inclusive finance. As Big Techs gain footing in the financial industry, will traditional lenders ultimately disappear? Or will traditional lenders coexist with Big Techs by catering to a differentiated clientele? The impact may vary across different traditional lenders.

In this paper, we focus on the impact of Big Tech on non-bank traditional lenders, which often serve borrowers with higher credit risks than banks and thus face more direct competition from Big Tech lending. Unlike banks, non-bank lenders do not take deposits, thus facing higher funding costs and finding their niche in serving a riskier clientele who banks may have rejected. Our proprietary data come from a car equity loan company with national branches in China. Our empirical methodology exploits geographical differences in penetration ratios of Big Tech lending and the opening time differences of the loan company's branches. To account for the learning-by-doing effect after a branch's opening, we construct a relative month measure to convert calendar months into branch-specific months relative to its opening month. We evaluate each branch's dynamic performance since its opening month and compare the differences between branches in cities with high penetration ratios of Big Tech credit and those in cities with low penetration ratios. Our estimates thus capture the differences between branches at the same development stage but with different intensities of Big Tech competition.

We expect borrowers in cities with higher penetration ratios of Big Tech credit to be more likely to borrow from Big Techs, which reduces the attractiveness of traditional loans. Interestingly, our ordinary-least squares (OLS) results show that branches in cities with higher Big Tech credit penetration would originate more loans in terms of the number of transactions and the total loan amount at a given relative month, indicating a positive correlation between Big Tech lending and traditional lending. One major caveat is that our OLS estimates are subject to the endogeneity problem; for instance, we may omit variables that affect both the Big Tech credit penetration and the performance of local branches of the traditional lending company, such as the time-varying economic conditions of different cities.

To address potential endogeneity problems, we use two instrumental variables (IVs): the great-circle distance to Hangzhou city, the Big Tech headquarter, and the penetration ratios of Big Tech payment services, which serve as a basis for Big Tech's lending businesses but do not directly compete with traditional lenders. Our IV estimates show that larger Big Tech credit penetration would reduce the number of loans originated by the traditional lender, consistent with our hypothesis that Big Tech credit relaxes households' borrowing constraints and weakens traditional lenders' competitiveness in the lending market. While we do not find evidence that the Big Tech competition induces local branches to lower the collateral requirement (measured by the average price of the collateral), we do find a reduction in the total amount of collateral values, corroborating our argument that branches facing more intense competition would experience a reduction in the number of borrowers.

Furthermore, the non-bank traditional lender responds to Big Tech competition by holding higher lending standards. Specifically, branches in cities highly penetrated by Big Tech credit would approve fewer amount loans per unit collateral value (defined as the loan-to-value ratios), implying a more prudent attitude towards qualified borrowers. We argue that this cautiousness in lending reflects traditional lenders' concern about the "cream-skimming" in the loan market by Big Techs, which may use more advanced FinTech to screen borrowers and "pick cherries" in the shared application pools. We also find that the increase in the lending standard pays off: the branches facing fiercer Big Tech competition do not experience higher default rates, indicating the success of the risk-control measures.

Our paper contributes to several strands of literature. First, our paper enriches the Big Tech credit literature by providing novel evidence of its impact on small- and medium-sized traditional lenders. Recently, there is a burgeoning literature on Big Tech credit (de la Mano and Padilla, 2018; Stulz, 2019; Frost et al., 2019; Padilla, 2020; Boissay et al., 2021; Beck et al., 2022; Huang et al., 2022). For instance, Gambacorta et al. (2022) examines two advantages of Big Techs compared to traditional banks: better information and better enforcement of credit repayment. Gambacorta et al. (2022) shows that big tech credit does not correlate with local housing prices but reacts strongly to changes in firm characteristics, thus reducing the importance of the collateral channel while introducing new volatilities. de la Mano and Padilla (2018) find that Big Tech platforms, while increasing competition in retail banking and benefiting financial consumers in the short term, may succeed in gaining monopoly power in lending while traditional banks merely become a funding source. Relatively understudied is the impact of Big Tech lending on smaller financial institutions. Our paper thus highlights the competitive impact of Big Tech credit and its implications on the market structure of the financial industry, such as the increasing concentration.

Second, we expand the research scope of FinTech and Big Tech lending by examining the impact on non-bank financial institutions (NBFIs), whose clientele is more exposed to FinTech lending than banks. An abundant literature has documented FinTech lender's disruptive impact on traditional banks (Goldstein et al., 2019; Buchak et al., 2021). Several papers also provide evidence that FinTech may complement traditional lending by targeting riskier borrowers and smaller-sized loans and through regulatory arbitrage (Buchak et al., 2018; Tang, 2019; Erel and Liebersohn, 2020). While previous studies mainly focus on the relationship between FinTech lenders and traditional banks, we investigate the impact of FinTech and Big Tech lending on non-bank lenders, which do not take deposits and hence face higher funding costs and less strict regulations than banks. As a result, their clientele is riskier than that of banks and therefore is more exposed to FinTech competition as FinTech lenders usually start by lending to unbanked borrowers. Adding to the existing literature, we show that non-bank traditional lenders experience a decline in the lending business. Our analysis of non-bank traditional lenders thus complements existing literature on the disruptive impact of FinTech lending on banks.

Third, we demonstrate the response of informationally-disadvantaged traditional lenders to Big Tech competition, echoing the classical literature on asymmetric information. Our empirical results show that non-bank traditional lenders adopt a more prudent lending standard, i.e., reducing the LTV ratios, to contain default rates. Interestingly, the interest rates charged by the lenders do not change and are restricted to a limited range. This quantity-based response is consistent with the credit rationing motive proposed by the seminal work of Stiglitz and Weiss (1981), where lenders find it optimal not to raise interest rates due to adverse selection and moral hazard concerns under asymmetric information.

Our paper proceeds as follows: Section 2 summarizes the institutional background of traditional and FinTech lending in China and describes the business details of the loan company in our sample. Section 3 details the data and presents our empirical methodology. In Section 4, we analyze the impact of Big Tech lending on the loan quality of traditional NBFIs. In Section 5, we conduct heterogeneity analysis and discuss our findings. We conclude in Section 6.

2 Institutional Background

2.1 The Rise of FinTech and Big Tech Lending in China

The definition of FinTech lending varies in different contexts. Still, it is usually based on a mix of features that include the characteristics of the customer-lender interaction and the screening and monitoring technology. The main practice of FinTech lending business includes Big Tech lending, P2P lending, as well as the digital transformation of banks.

Big Tech lending. The business model of Big Tech lending started and took off in China. A typical example is the "3-1-0" credit model created by Alibaba which originates loans to online business owners relying on its e-commerce platform and ecosystem. The term "3-1-0" refers to the fact that customers only need 3 minutes to apply for a loan online. If approved, the funds will reach the borrower's Alipay account within 1 second, with the whole process of 0 manual intervention. The scale of China's Big Tech credit ranks first in the world. The top digital banks in China, such as WeBank and MYbank, can issue millions or even tens of millions of loans yearly, with the average non-performing loan ratio remaining at 1%-2%, far lower than the non-performing rate of SME loans of traditional commercial banks.

P2P lending. The development of P2P lending in China began in 2007 and experienced its infancy, growth and prosperity, collapse and contraction, and finally, a complete exit in the following 13 years. From 2007 to 2012, P2P lending in China was not a large market. By the end of 2012, there were 150 platforms in normal operation, and the balance of online lending was 21.2 billion yuan. From 2013 to 2015, online lending platforms began to experience explosive growth, and the number of normal operating platforms soared from 586 at the end of 2013 to 3,433 in 2015. In December 2015, the regulatory authorities released the regulatory rules for P2P lending for the first time, and then the number of online lending platforms began to decline. At the end of 2017, the loan balance of the online lending industry reached its peak of 1.3 trillion yuan, and the annual transaction amount was 2.7 trillion yuan. In January 2019, the regulatory authorities issued the "Opinions on Classifying and Disposing of Online Lending Institutions and Risk Prevention," proposing that problematic P2P lending institutions should be shut down. At the end of 2020, all P2P platforms have been cleared.

Digital transformation of banks. To compete with the new FinTech institutions, traditional commercial banks have also invested heavily in digital technology. The digital transformation of banks includes multiple dimensions, including the managerial cognition of financial technology, organizational changes, and the development of digital products. Among the digital products developed by banks, online lending is an important category. Of the 18 state-owned and joint-stock banks in China, only 3 had online lending products in 2010, while all 18 banks launched their own online lending products in 2018. Since the entire lending process must be carried out on an online platform, a powerful and robust system needs to be built. Thus, state-owned banks are ahead of joint-stock banks in developing online lending.

2.2 Non-bank Traditional Lenders in China

For SMEs and low- to middle-income families in China, the availability of loans from commercial banks is often insufficient prior to the rise of FinTech and Big Tech lending. These borrowers have to obtain loans from other financial institutions, and micro-loan companies play an important role in serving these credit-constrained groups. Among the business model of micro-finance companies, car equity loans are a typical one, in which the borrower uses a car as collateral to apply for a loan. This model can be divided into two types. One is that the mortgaged vehicle must be parked in a specific garage, and the borrower cannot use the vehicle before repayment. The other is that the lender installs a GPS in the mortgaged vehicle to locate the vehicle so that the vehicle can be disposed of after a default, and the borrower can retain the use of the vehicle. For enterprises with relatively sufficient assets, the former is acceptable. For many borrowers, especially SME owners, however, their vehicles are important commuting tools in their daily life or production tools for purchase and delivery, so only the latter model is feasible.

The loan company we examine in this paper adopts the latter lending model and operates through local brick-and-mortar branches. The company launched its first microloan product in May 2015 and gradually expanded its branch network to a nationwide presence. Figure 3 illustrates the opening months of the earliest branches in each prefecture-level city or municipality. Most of the company's funds came from P2P platforms, and a small part came from banks, insurance companies, trusts, and other financial institutions. The borrowers were mainly SME owners and self-employed individuals, who were not covered by the traditional banking industry.

In terms of the loan application and decision process, when a borrower applies for a loan at an offline store, the officer determines the loan amount based on the information submitted and the condition of the vehicle collateral. Specifically, the approved loan amount is the product of 1) the third-party appraised value of the loan applicant's mortgaged vehicle and 2) the loan-to-value ratio determined by the officer based on the applicant's information and historical records. A higher loan ratio corresponded to a lower risk level for the borrower.

In terms of loan product selection, the borrower only needed to decide on the amount he would apply, and the officer would recommend standardized products for the borrower, with an interest rate, loan term, and loan payment schedule uniformly set. There were two types of loan payment schedules: even a total payment or a balloon payment that borrowers paid the interest every month and repaid all the principal when the loan was due. Each loan product was standardized so that its interest rate, loan term, and loan payment schedules were identical for all applicants choosing it. The interest rate of the loan product would be adjusted according to the market conditions, but do not vary across different borrowers.

It is worth noting that the customers of microloan companies are most likely different from those of commercial banks but may have a large overlap with big tech companies. For example, since the examined microloan company used vehicles as collateral, the application amount and approval amount for each loan were quite small in scale, both less than 100,000 yuan. In contrast, the People's Bank of China (PBOC) uses "single-account credit less than 10 million yuan" as the standard for assessing banks' small and micro-enterprise loans. However, if we look at WeBank, the digital bank owned by Tencent, the average loan amount they granted to their customers of SME owners is about 270,000 yuan, which is much closer to traditional microloans in terms of loan size.

The regulatory requirements of microfinance companies are also different from those of commercial banks in China. On May 8, 2008, the China Banking Regulatory Commission (CBRC) and the PBOC issued the "Guiding Opinions on the Pilot Program of Small Loan Companies," which stipulates the nature, establishment, source, and use of funds and other related issues of small loan companies. In 2020, the China Banking and Insurance Regulatory Commission issued the "Notice on Strengthening the Supervision and Management of Small Loan Companies," emphasizing the need to strengthen supervision and management and rectify the order of the microloan industry. Since 2015, due to factors such as economic growth downshifting, corporate deleveraging, and the regulation of microloan companies, the number, and scale of microloan companies have been declining.

3 Data and Empirical Methodology

3.1 Data Sources

Our data mainly come from the vehicle mortgage loan company described in Section 2 from September 2015 to November 2017. The dataset contains six types of information: (1) loan application information including the borrower ID, the application date, and the application loan amount; (2) loan contract characteristics, including the origination store, loan approval date, approved loan amounts, loan product types, maturities, monthly interest rates, the method of repayment. LTV ratios refer to the ratio dividing the approved amount by the assessed price of the car and serve as an instrument decided by the loan company to control the risk; (3) loan performance information, including maximum default days; (4) borrower characteristics such as age, gender, education level, marriage situation, and monthly income; (5) car characteristics such as the brand, the mileage, the assessed value, and the license number; and (6) origination store characteristics, including the address and the loan manager in charge.

3.2 The Analytical Sample

Sample period: We obtain the entire lending history of the lender as of March 2019, which contains 216,647 observations since its first loan in May 2014. We drop 49,749 observations in and after December 2017 since the loan contracts in that period would be influenced by FinTech directly.

Data cleaning: To exclude recording errors, we drop 19,961 outlier observations with assessed prices or approved amounts exceeding 20,0000 or below 1,000 and with no assessed prices. We exclude from our sample 6 observations whose approved amount is more than the assessed price of the collateral. We drop all 68 observations from Datong city and 1 observation from Suqian city since the maximum default days in the city all exceed 30 days, making the city an outlier in terms of default rates. We also drop 216 observations from Jiyuan city, which is a county-level city and our research only focuses on prefecture-level cities and municipalities directly under the central government.

Since in early-stage, the lender has been exploring the business model and in December 2017 the company introduced FinTech big data when doing business, we only keep loan contracts from 206 stores which are active from April 2016 to November 2017. Our final sample for the analysis contains 146,565 loan-level observations between September 2015 to November 2017 in 206 stores around the nation.

3.3 Variable Construction

LTV ratios. We calculate LTV ratios as the approved amount divided by the assessed price of collateral, which is the actual index for the company to control risk. In the dataset, there is a variable named "reported proportion", which results from rounding the LTV ratios to one decimal place.

Default. We define a variable Default to measure the ex-post repayment situation. If the maximum number of default days is more than 30 days, we define Default as equal to one, otherwise equal to zero.

We treat the month of the branch's first loan contract after dropping outliers as the opening time of the branch. For each branch, we define the variable "Month" to measure the time of the loan relative to the opening month of the store. For the opening month of the store, the variable Month equals one.

To identify the level of Big Tech penetration credit business in the city where the branch is open if the opening month falls between January and June, we use the sub-index credit from last year and if the opening month is between July and December, we use sub-index credit in that year. For instance, if the branch opened in March 2016, the sub-index credit matched is the corresponding value of the city in 2015; if the branch opened in August 2016, the sub-index credit matched is the corresponding value of the city in 2016. Then we standardize the sub-index credit by dividing it by 100 and name the variable after standardizing "Credit".

For each branch and month of business, we calculate the number of loan contracts, the total amount of loans, and the total and average assessed price of collaterals, taking a logarithm of them. We also calculate the simple average and weighted averages by loan amount of LTV ratios and default situation in each branch and active month.

We use the license number of the cars and the location of the branches to identify whether the location of the vehicle license is the same city as the branch. If they are in the same city, we define the borrowers to use a local car for lending; otherwise, they use a nonlocal car for a mortgage. For each branch and each month, we define the variable "Local" to measure the proportion of local cars.

Finally, our sample is panel data and contains monthly business situations at the store level, including 47 stores in 2015, 122 stores in 2016, and 206 stores in 2017.

3.4 Descriptive Analysis

Figure 1 plots the time trend of the Big Tech penetration index, including the aggregate index and sub-index of usage depth on credit, which show that 2015 was a booming year for digital finance and Big Tech credit. Panel A in figure 3 shows the opening time of different branches with sub-index credit in their located cities in 2014, indicating that our sample company began to open branches across the country in 2015 and the first batch of branches are concentrated in the cities with high credit, then gradually expand to cities with low credit. Panel B in figure 3 plots the credit level close to the opening month and opening month of each branch. Since sub-index credit has generally increased over time, the later the city opens, the higher the credit at the time of opening. This difference and time trend can be solved by controlling the branch fixed effects (including the opening time of each branch) and year-month fixed effects in empirical analysis. When we define the variable "Credit", if a branch opened from July 2016 to June 2017, the variable "Credit" is the sub-index credit in 2016. Thus, comparing the branches that opened during this period together, we can still find that branches opening first have a high credit index.

In terms of geographical space, the distribution of stores of this traditional loan company we studied overlaps greatly with the distribution of credit penetration rate of Big Tech, which may be affected by the competition of Big Tech credit.

Table 1 provides summary statistics of the main variables in our regression sample. For all branches active before November 2017, the maximum number of the opening month is 27 and on average, the number is about 10. For the business of each branch in one month, on average the number of loans is 50.54, the total amount of loans is 3,000,000, the total assessed price of collateral is 4,000,000 and the average collateral value is 81,188. The simple average and weighted average by amount of loan of LTV ratios are 0.747 and 0.761. The simple average and weighted average by loan amount of default rate are 0.151 and 0.150. The average ratio of local cars for each store every month is 0.876, which means about 87.6% of loan contracts use local cars as collateral.

3.5 Empirical Methodology

Big Tech credit focuses on credit loans and does not require collateral. Our sample company is a car equity loan company. The two don't appear to compete directly in terms of product or customer base. When will the competition occur? It is the customers who used to rely on traditional finance to get loans, but now they can get financing through Big Tech credit. In theory, Big Tech digitalizes various information and captures big data. Thus, it reduces the value of soft information in lending and weakens the advantage of small local lenders. This may lead to the loss of high-quality customers and the sinking of the customer base of the sample company (such as the default rate rising).

We compare the business situation after opening through the difference in the Big Tech penetration index of different branches. How will the borrowers choose? Will there be high-risk people who come to borrow? The baseline panel data regression equation is as follows

$$Y_{it} = \alpha + \beta Credit_i * Month_{it} + \gamma_{ym} + \delta_i + \eta X_{it} + \epsilon_{it} \quad (1)$$

where i indexes the branch and t is the relative month to the opening time of each branch. Y_{it} are outcomes for each branch. $Credit_i$ is the sub-index "credit" from the Peking University Digital Financial Inclusion Index of China (PKU-DFIIC), showing the usage depth of credit operations divided by 100. $Month_{it}$ is the relative month to the opening time of each branch. For each branch, in their opening month, $Month_{it}$ equals one. γ_{ym} and δ_j are year-month of the Gregorian calendar and branch fixed effects, respectively. X_{it} are control variables for the located city, including the logarithm of GDP and population times a relative month.

Since the Big Tech penetration index is at the municipal level, cities' economic situation may influence both the level of Big Tech penetration and the availability of loans, thus there might be endogeneity problems. We use instrument variables to solve the problem.

$$Y_{it} = \alpha + \beta Credit_i * Month_{it} + \gamma_{ym} + \delta_i + \eta X_{it} + \epsilon_{it} \quad (2)$$

$$Credit_i * Month_{it} = \theta + \mu Z_i * Month_{it} + \gamma_{ym} + \delta_i + \eta X_{it} + \epsilon_{it} \quad (3)$$

where Z_i is the instrument variable. We chose the distance from the city to Hangzhou or sub-index payment in 2015 as the instrument variable. The distance between the two cities is decided by the administrative division, which does not change and is not affected by the development situation. However, the distance to Hangzhou, which is the center of digital finance development, can show the development potential of Big Tech penetration. Sub-index payment in 2015 reflects people' s usage of online payments and influences lending only through the level of digital finance. Thus, the two instrument variables are both exogenous and correlative.

4 Main Results

We want to know the overall business situation of the company first. Table 2 shows the changes in the number (Columns (1)-(3)) and the total amount of loans (Columns (4)-(6))

per month with a different beginning level of Big Tech penetration over time. For the key variable, we focus on –credit times the relative months –in panel data OLS regression, the coefficient of the interaction term for number is 0.049 and for the total amount is 0.052 as shown in Columns (1) and (4), respectively, which are both significantly positive. However, after using instrumental variables to solve the endogenous problem, the coefficient of interaction term becomes significantly negative, which means if the branch locates in a city with a higher Big Tech penetration credit level, the number and total amount of loan contracts fall even faster, indicating that in a location with higher Big Tech penetration, Big Tech credit is more competitive with traditional mortgages and squeezes out more business.

The value of the collateral is an important factor in mortgage loans. Thus, we pay attention to the assessed price of cars used as collateral. Columns (1)-(3) of Table 3 report the results of the total assessed price, and Columns (4)-(6) present the situation of the average assessed price. The coefficient of the interaction term ($Credit \times Month$) is significantly negative in IV regressions for the total assessed price shown in Columns (2) and (3). The results indicate that if the branch is located in a city with a higher level of sub-index credit, the total value of loan collateral each month drops faster with longer lending months. This may be due to the number of loans, so we examine the impact on the average assessed price of cars used as collateral each month. There is no significant difference in branches with different Big Tech penetration. The requirements of lenders on the value of their mortgaged vehicles have not fallen.

For LTV ratios –the most important indicator to control risk in the company –the coefficient of the interaction term ($Credit \times Month$) are -0.007 in Column (2)-(3) and -0.008 in Column (5)-(6), which are all significantly negative and shows in table 4. We find both simple average and weighted average (weighted by loan amount) LTV ratios decrease faster in branches with higher sub-index credit, which is because with higher sub-index credit, the competition from Big Tech companies is even fiercer and the borrowers that get loans from the company are riskier even if they use the similar value of collateral, thus the platform chooses lower average LTV ratios to control risk.

As for the ex-post situation, we consider the default rate for each branch's business. There is also no significant difference among branches with different levels of Big Tech penetration, which can be seen from table 5. This also confirms the rationality of the difference in LTV ratios.

5 Further Analysis

Big Tech credit mainly focuses on credit loans, among which relationship loans occupy an important position. The geographical relationship between people and the branch plays a big role, and the branch can get more soft information about locals. However, in cities with a high level of Big Tech penetration, Big Tech credit is more convenient and borrowers will be disclosed more information, so the advantage of branches in obtaining locals' soft information when lending reduces. Based on this analysis, the competitive impact of Big Tech credit is greater when branches accept more local cars as loan collateral. We used the percentage of local car branches receiving for heterogeneity analysis.

Table 6 shows the heterogeneity in the number and total amount of loans. We can find that if borrowers use more local cars as collateral, the negative effect of Big Tech competition on the branches of this company will be higher, since the coefficient of the triple cross term ($Credit \times Month \times Local$) are significantly negative and the coefficient of the interaction term ($Credit \times Month$) are significantly positive in Column (3) and (6). As for the assessed price, the total price for each branch in a month will be influenced by the percentage of local cars, but for the average assessed price, there is no significant difference, which can be seen in table 7. The results present the same conclusion as before that the difference in total assessed price is due to the number of loans in each branch every month. However, the requirement for the value of the collateral on each loan has not changed.

However, as reported in table 8, if more borrowers use local cars as collateral, the decline in the simple average and weighted average (weighted by loan amount) LTV ratios is smaller. Columns (2)-(3) show that the coefficients of the triple cross term ($Credit \times Month \times Local$) are significantly positive, while Columns (5)-(6) show that coefficients of the interaction term ($Credit \times Month$) are significantly negative. This may be because owners of local cars have more social connections and the cost of default is higher, so using local cars as collateral will be expected to have a lower default rate and the branch gives them higher LTV ratios. When faced with Big Tech credit competition, branches with a large number of local borrowers do not need to significantly reduce the LTV ratio to control risk. Thus, branches with a higher percentage of local cars are less likely to be affected by competition with Big Tech credit in LTV ratios on average.

6 Conclusion

The rise of Big Tech lending has changed the competitive landscape faced by traditional lenders. Using the Big Tech penetration index and proprietary data from a traditional loan company in China, we investigate the impact of Big Tech competition by exploiting geographical differences in Big Tech penetration and the opening time differences of the loan company's branches. We use two IVs to address endogeneity issues: Big Tech payment adoption and the distance to Hangzhou city, the Big Tech's headquarter. Our regression results show that branches in cities with higher Big Tech credit penetration ratios experience a larger decline in the lending business, with fewer successful borrowers and a lower amount of originated loans. While there is little impact on the average collateral requirement, branches facing greater Big Tech competition tighten their lending standards by reducing the LTV ratios, measured as the approved loan amount per unit collateral value.

Our findings are consistent with the hypothesis that Big Techs with more advanced screening technology lead to cream-skimming in the loan market, worsening the borrower pool faced by traditional lenders. While Big Tech lending generally improves social welfare by reducing informational asymmetry, relaxing the collateral constraint, and promoting inclusive finance, its impact on the traditional lending business, especially small- and medium-sized banks (SMBs) and non-bank financial institutions (NBFIs), is worth further investigation to derive a comprehensive understanding of the opportunities and challenges in the Big Tech era.

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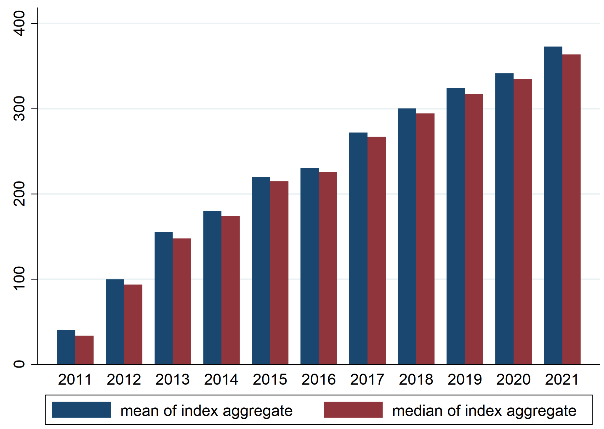
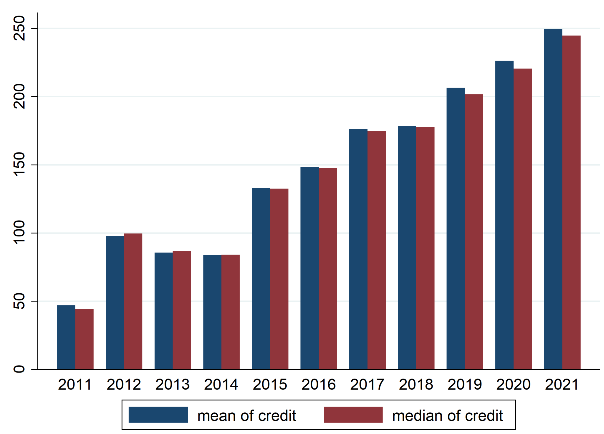
Figure 1: Time Trend of Big Tech Penetration

Note: This figure plots the time trend of Big Tech penetration ratios measured by the Peking University Digital Financial Inclusion Index of China (PKU-DFIIC), including the average and median of the aggregate index, coverage breadth, usage depth, digitization level, and credit at the provincial level from 2011 to 2021, respectively.



(a) Aggregate index



(b) Credit

Figure 2: Opening Time of Local Branches

Note: The figure shows the opening month of the earliest branches at the prefecture-level. In this figure, 1 is November 2018, 2 is January 2018, 3 is December 2017, 4 is November 2017, 5 is October 2017, 6 is September 2017, 7 is August 2017, 8 is July 2017, 9 is June 2017, 10 is May 2017, 11 is April 2017, 12 is March 2017, 13 is November 2016, 14 is October 2016, 15 is August 2016, 16 is July 2016, 17 is June 2016, 18 is May 2016, 19 is April 2016, 20 is March 2016, 21 is January 2016, 22 is December 2015, 23 is November 2015 and 24 is September 2015. The missing month is because no branches are opening. "No data" means the platform has no branches in the city.

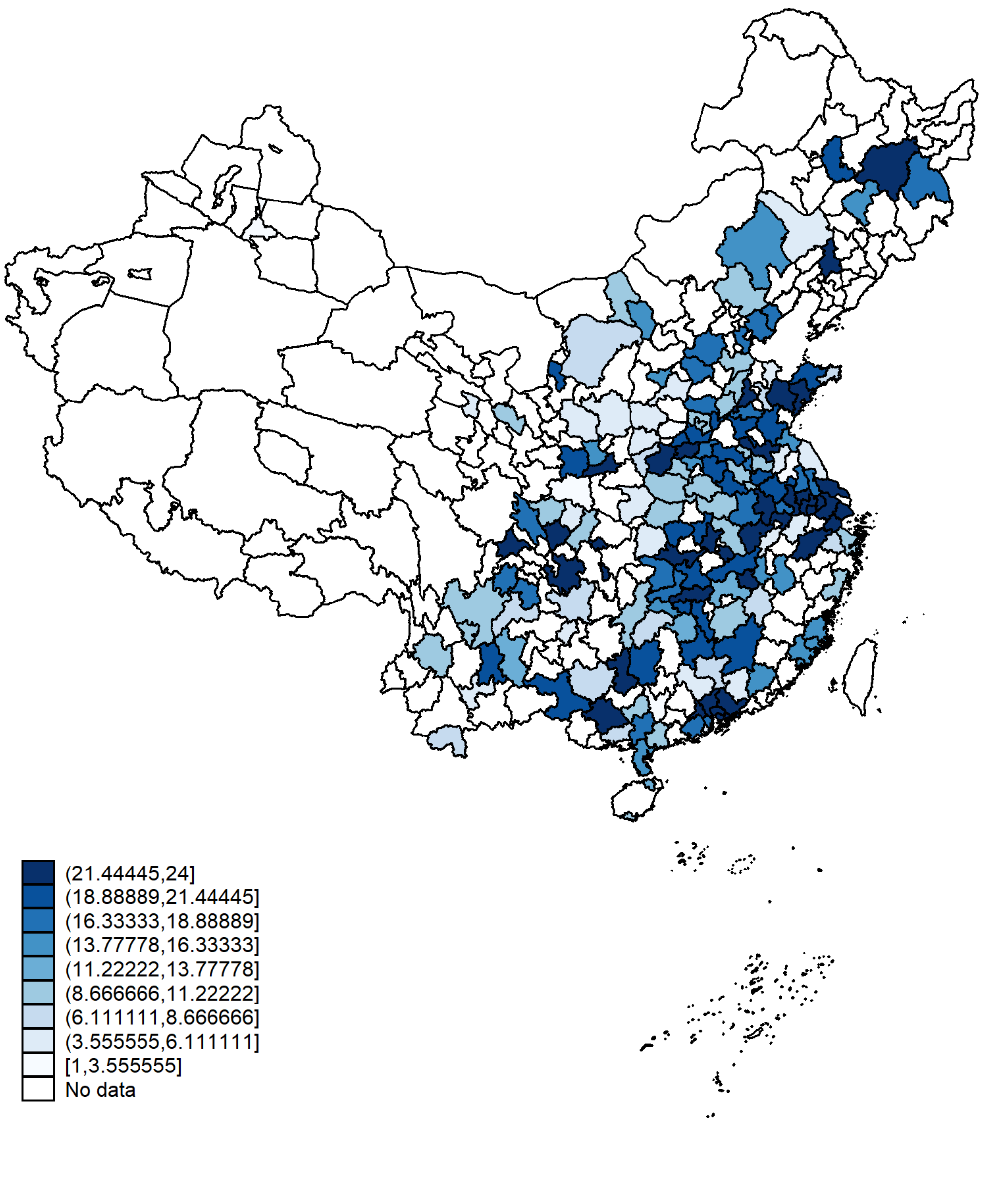
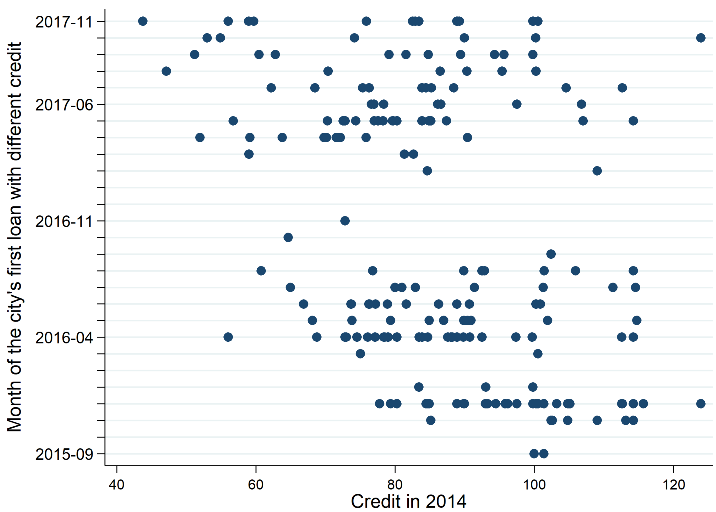
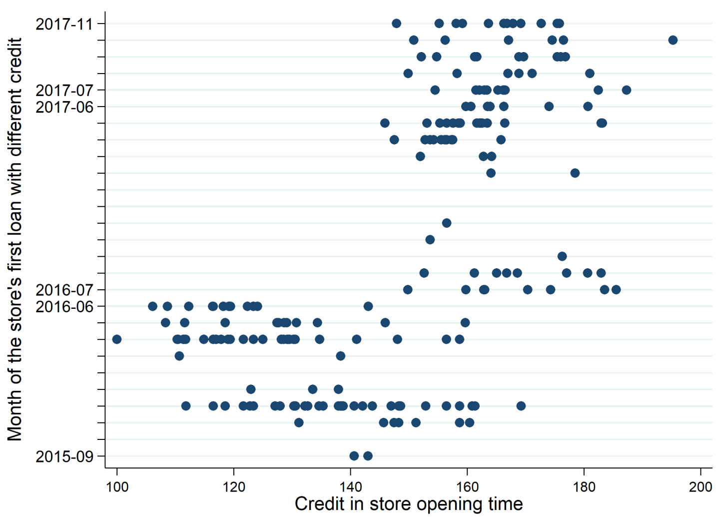


Figure 3: Local Branches and Big Tech Credit Penetration Index

Note: This figure plots the opening time of different branches. Panel A shows the opening time of different branches with Big Tech credit penetration ratios in their located cities in 2014, and panel B shows the Big Tech credit penetration level close to the opening month and opening month of each branch.



(a) Opening month with Big Tech credit penetration in 2014



(b) Opening month with Big Tech credit penetration around opening time

Table 1: Summary Statistics

Note: This table reports summary statistics of the regression sample. The sample contains 206 branches from September 2015 to November 2017 around the whole country, including 47 branches in 2015, 122 branches in 2016, and 206 branches in 2017. All variables are calculated at the branch level each month.

	N	Mean	Sd	min	max	p25	P50	p75
Month	2,900	9.923	6.462	1	27	4	9	15
Number	2,900	50.54	31.08	1	240	28	46	68
Number(log)	2,900	3.673	0.835	0	5.481	3.332	3.829	4.220
Amount	2,900	3.003e+06	1.835e+06	20,000	1.462e+07	1.691e+06	2.769e+06	4.035e+06
Amount(log)	2,900	14.66	0.854	9.903	16.50	14.34	14.83	15.21
Price	2,900	4.080e+06	2.528e+06	31,000	2.145e+07	2.285e+06	3.727e+06	5.451e+06
Price(log)	2,900	14.97	0.851	10.34	16.88	14.64	15.13	15.51
Average price	2,900	81,188	11,944	31,000	200,000	74,431	81,058	87,413
Average price(log)	2,900	11.29	0.145	10.34	12.21	11.22	11.30	11.38
LTV ratios(Simple average)	2,900	0.747	0.0435	0.345	1	0.722	0.747	0.773
LTV ratios(weighted average)	2,900	0.761	0.0405	0.345	1	0.739	0.761	0.784
Default rate	2,900	0.151	0.211	0	1	0.0455	0.0882	0.156
Default rate(weighted average)	2,900	0.150	0.214	0	1	0.0394	0.0846	0.158
Local	2,899	0.876	0.148	0	1	0.833	0.920	0.976

Table 2: Overall Business

Note: This table reports the results of the following regression

$$Y_{it} = \alpha + \beta Credit_i * Month_{it} + \gamma_{ym} + \delta_i + \eta X_{it} + \epsilon_{it} \tag{1}$$

$$Credit_i * Month_{it} = \theta + \mu Z_i * Month_{it} + \gamma_{ym} + \delta_i + \eta X_{it} + \epsilon_{it} \tag{2}$$

This table reports the changes in the number and amount of loans among branches with different credit levels based on panel data regression. Y_{it} is the logarithm of the number and the total amount of loans for each branch in every active month. $Credit_i$ is sub-index credit around the branch's opening time divided by 100. $Month_{it}$ is the relative month to the opening time of each branch. Z_i is the instrument variable. In columns (2) and (5), Z_i is the logarithm of distance to Hangzhou, and in columns (3) and (6), Z_i is the sub-index payment in 2015. X_{it} are control variables, including the logarithm of GDP and population times a relative month. δ_j and γ_{ym} denote branch fixed effects and year-month fixed effects, respectively, and ϵ_{it} represents the error term. Standard errors are adjusted for robustness and reported in parentheses. ***, **, * denote significance levels at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
		Number(log)			Amount(log)	
	OLS	IV1	IV2	OLS	IV1	IV2
Credit × Month	0.049*	-0.197***	-0.077**	0.052**	-0.209***	-0.086**
	(0.026)	(0.063)	(0.039)	(0.026)	(0.065)	(0.041)
GDP(log) × Month	-0.020**	0.013	-0.003	-0.022***	0.014	-0.002
	(0.008)	(0.010)	(0.007)	(0.008)	(0.010)	(0.007)
Population(log) × Month	0.019*	-0.014	0.003	0.021*	-0.014	0.003
	(0.011)	(0.011)	(0.008)	(0.012)	(0.011)	(0.008)
Branch FE	YES	YES	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES	YES	YES
Observations	2,900	2,862	2,888	2,900	2,862	2,888
R-squared	0.259	0.151	0.228	0.250	0.135	0.215
Number of branches	206	192	194	206	192	194

Table 3: Collateral Value

Note: This table reports the results of the following regression

$$Y_{it} = \alpha + \beta Credit_i * Month_{it} + \gamma_{ym} + \delta_i + \eta X_{it} + \epsilon_{it} \quad (3)$$

$$Credit_i * Month_{it} = \theta + \mu Z_i * Month_{it} + \gamma_{ym} + \delta_i + \eta X_{it} + \epsilon_{it} \quad (4)$$

This table reports the changes in the assessed price of collateral among branches with different credit levels based on panel data regression. Y_{it} is the logarithm of the total and average assessed price of loans' collateral for each branch in every active month. $Credit_i$ is sub-index credit around the branch's opening time divided by 100. $Month_{it}$ is the relative month to the opening time of each branch. Z_i is the instrument variable. In columns (2) and (5), Z_i is the logarithm of distance to Hangzhou and in columns (3) and (6), Z_i is the sub-index payment in 2015. X_{it} are control variables, including the logarithm of GDP and population times a relative month. δ_j and γ_{ym} denote branch fixed effects and year-month fixed effects, respectively, and ϵ_{it} represents the error term. Standard errors are adjusted for robustness and reported in parentheses. ***, **, * denote significance levels at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Total price(log)			Average price(log)		
	OLS	IV1	IV2	OLS	IV1	IV2
Credit × Month	0.052**	-0.199***	-0.078*	0.003	-0.002	-0.000
	(0.027)	(0.065)	(0.041)	(0.003)	(0.012)	(0.006)
GDP(log) × Month	-0.023***	0.012	-0.005	-0.002***	-0.002	-0.002*
	(0.008)	(0.010)	(0.007)	(0.001)	(0.002)	(0.001)
Population(log) × Month	0.022*	-0.012	0.005	0.003**	0.002	0.002*
	(0.012)	(0.011)	(0.008)	(0.001)	(0.002)	(0.001)
Branch FE	YES	YES	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES	YES	YES
Observations	2,900	2,862	2,888	2,900	2,862	2,888
R-squared	0.255	0.148	0.224	0.064	0.063	0.063
Number of branches	206	192	194	206	192	194

Table 4: LTV ratios

Note: This table reports the results of the following regression

$$Y_{it} = \alpha + \beta Credit_i * Month_{it} + \gamma_{ym} + \delta_i + \eta X_{it} + \epsilon_{it} \tag{5}$$

$$Credit_i * Month_{it} = \theta + \mu Z_i * Month_{it} + \gamma_{ym} + \delta_i + \eta X_{it} + \epsilon_{it} \tag{6}$$

This table reports the changes in LTV ratios among branches with different credit levels based on panel data regression. Y_{it} is the simple average and weighted average by loan amount of LTV ratios for each branch in every active month. $Credit_i$ is sub-index credit around the branch's opening time divided by 100. $Month_{it}$ is the relative month to the opening time of each branch. Z_i is the instrument variable. In columns (2) and (5), Z_i is the logarithm of distance to Hangzhou, and in columns (3) and (6), Z_i is the sub-index payment in 2015. X_{it} are control variables, including the logarithm of GDP and population times a relative month. δ_j and γ_{ym} denote branch fixed effects and year-month fixed effects, respectively, and ϵ_{it} represents the error term. Standard errors are adjusted for robustness and reported in parentheses. ***, **, * denote significance levels at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Simple average			Weighted average		
	OLS	IV1	IV2	OLS	IV1	IV2
Credit × Month	-0.000	-0.007**	-0.007***	-0.001	-0.008***	-0.008***
	(0.001)	(0.003)	(0.002)	(0.001)	(0.003)	(0.002)
GDP(log) × Month	0.001**	0.002***	0.002***	0.001**	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Population(log) × Month	-0.000	-0.001***	-0.001***	-0.000	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Branch FE	YES	YES	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES	YES	YES
Observations	2,900	2,862	2,888	2,900	2,862	2,888
R-squared	0.277	0.260	0.252	0.325	0.300	0.289
Number of branches	206	192	194	206	192	194

Table 5: Default Rate

Note: This table reports the results of the following regression

$$Y_{it} = \alpha + \beta Credit_i * Month_{it} + \gamma_{ym} + \delta_i + \eta X_{it} + \epsilon_{it} \quad (7)$$

$$Credit_i * Month_{it} = \theta + \mu Z_i * Month_{it} + \gamma_{ym} + \delta_i + \eta X_{it} + \epsilon_{it} \quad (8)$$

This table reports the changes in default rate among branches with different credit levels based on panel data regression. Y_{it} is the simple average and weighted average by loan amount of default rate for each branch in every active month. $Credit_i$ is sub-index credit around the branch's opening time divided by 100. $Month_{it}$ is the relative month to the opening time of each branch. Z_i is the instrument variable. In columns (2) and (5), Z_i is the logarithm of distance to Hangzhou, and in columns (3) and (6), Z_i is the sub-index payment in 2015. X_{it} are control variables, including the logarithm of GDP and population times a relative month. δ_j and γ_{ym} denote branch fixed effects and year-month fixed effects, respectively, and ϵ_{it} represents the error term. Standard errors are adjusted for robustness and reported in parentheses. ***, **, * denote significance levels at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Simple average			Weighted average		
	OLS	IV1	IV2	OLS	IV1	IV2
Credit × Month	0.003	-0.014	-0.004	0.003	-0.013	-0.003
	(0.002)	(0.009)	(0.004)	(0.002)	(0.009)	(0.005)
GDP(log) × Month	-0.000	0.002*	0.001	0.000	0.002	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Population(log) × Month	0.000	-0.002	-0.001	0.000	-0.002	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Branch FE	YES	YES	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES	YES	YES
Observations	2,900	2,862	2,888	2,900	2,862	2,888
R-squared	0.885	0.878	0.884	0.869	0.862	0.868
Number of branches	206	192	194	206	192	194

Table 6: Heterogeneity in Overall Business

Note: This table reports the results of the following regression

$$Y_{it} = \alpha + \beta_1 Credit_i * Month_{it} + \beta_2 Credit_i * Month_{it} * Local_{it} \quad (9)$$
$$+ \beta_3 Local_{it} + \beta_4 Credit_i * Local_{it} + \beta_5 Month_{it} * Local_{it} \quad (10)$$
$$+ \gamma_{ym} + \delta_i + \eta X_{it} + \epsilon_{it} \quad (11)$$

$$W_{it} = \theta + \mu_1 Z_i * Month_{it} + \mu_2 Z_i * Month_{it} * Local_{it} \quad (12)$$
$$+ \mu_3 Z_i * Local_{it} + \gamma_{ym} + \delta_i + \eta X_{it} + \epsilon_{it} \quad (13)$$

This table reports the heterogeneous changes in the number and amount of loans among branches with different credit levels based on panel data regression. Y_{it} is the logarithm of the number and the total amount of loans for each branch in every active month. $Credit_i$ is sub-index credit around the branch's opening time divided by 100. $Month_{it}$ is the relative month to the opening time of each branch. $Local_{it}$ is the percentage of local cars in each branch' s monthly loan contracts. W_{it} includes $Credit_i * Month_{it}$, $Credit_i * Month_{it} * Local_{it}$ and $Credit_i * Local_{it}$. Z_i is the instrument variable. In columns (2) and (5), Z_i is the logarithm of distance to Hangzhou, and in columns (3) and (6), Z_i is the sub-index payment in 2015. X_{it} are control variables, including the logarithm of GDP and population times a relative month. δ_j and γ_{ym} denote branch fixed effects and year-month fixed effects, respectively, and ϵ_{it} represents the error term. Standard errors are adjusted for robustness and reported in parentheses. ***, **, * denote significance levels at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
		Number(log)			Amount(log)	
	OLS	IV1	IV2	OLS	IV1	IV2
Credit × Month	0.338**	0.979	0.931***	0.312**	0.861	0.889***
	(0.144)	(0.617)	(0.198)	(0.158)	(0.650)	(0.203)
Credit × Month × Local	-0.337**	-1.358**	-1.160***	-0.304*	-1.229*	-1.119***
	(0.160)	(0.662)	(0.212)	(0.176)	(0.695)	(0.218)
Local	-4.477	-10.329	-19.239***	-3.962	-11.333	-20.559***
	(3.733)	(10.772)	(4.834)	(4.401)	(12.756)	(5.277)
Credit × Local	3.059	6.664	12.717***	2.780	7.414	13.658***
	(2.335)	(6.938)	(3.190)	(2.710)	(8.218)	(3.495)
Month × Local	0.471*	1.981**	1.696***	0.416	1.782*	1.628***
	(0.245)	(1.010)	(0.332)	(0.273)	(1.059)	(0.341)
GDP(log) × Month	-0.023***	0.009	-0.006	-0.024***	0.008	-0.006
	(0.008)	(0.010)	(0.006)	(0.008)	(0.010)	(0.006)
Population(log) × Month	0.017	-0.023**	-0.007	0.020*	-0.021**	-0.005
	(0.011)	(0.010)	(0.007)	(0.012)	(0.010)	(0.008)
Branch FE	YES	YES	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES	YES	YES
Observations	2,899	2,861	2,887	2,899	2,861	2,887
R-squared	0.262	0.080	0.180	0.250	0.083	0.161
Number of branches	206	192	194	206	192	194

Table 7: Heterogeneity in Collateral Value

Note: This table reports the results of the following regression

$$Y_{it} = \alpha + \beta_1 Credit_i * Month_{it} + \beta_2 Credit_i * Month_{it} * Local_{it} \tag{14}$$
$$+ \beta_3 Local_{it} + \beta_4 Credit_i * Local_{it} + \beta_5 Month_{it} * Local_{it} \tag{15}$$
$$+ \gamma_{ym} + \delta_i + \eta X_{it} + \epsilon_{it} \tag{16}$$

$$W_{it} = \theta + \mu_1 Z_i * Month_{it} + \mu_2 Z_i * Month_{it} * Local_{it} \tag{17}$$
$$+ \mu_3 Z_i * Local_{it} + \gamma_{ym} + \delta_i + \eta X_{it} + \epsilon_{it} \tag{18}$$

This table reports the heterogeneous changes in the assessed collateral price among branches with different credit levels based on panel data regression. Y_{it} is the logarithm of the total and average assessed price of loans' collateral for each branch in every active month. $Credit_i$ is sub-index credit around the branch's opening time divided by 100. $Month_{it}$ is the relative month to the opening time of each branch. $Local_{it}$ is the percentage of local cars in each branch's monthly loan contracts. W_{it} includes $Credit_i * Month_{it}$, $Credit_i * Month_{it} * Local_{it}$ and $Credit_i * Local_{it}$. Z_i is the instrument variable. In columns (2) and (5) Z_i is the logarithm of distance to Hangzhou and in columns (3) and (6) Z_i is the sub-index payment in 2015. X_{it} are control variables including the logarithm of GDP and population times a relative month. δ_j and γ_{ym} denote branch fixed effects and year-month fixed effects, respectively, and ϵ_{it} represents the error term. Standard errors are adjusted for robustness and reported in parentheses. ***, **, * denote significance levels at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Total price(log)			Average price(log)		
	OLS	IV1	IV2	OLS	IV1	IV2
Credit × Month	0.328**	1.020	0.933***	-0.011	0.041	0.002
	(0.147)	(0.657)	(0.203)	(0.021)	(0.154)	(0.052)
Credit × Month × Local	-0.322**	-1.395**	-1.161***	0.015	-0.037	-0.000
	(0.163)	(0.702)	(0.218)	(0.024)	(0.163)	(0.056)
Local	-4.394	-13.838	-20.566***	0.084	-3.509	-1.327
	(3.905)	(12.495)	(5.178)	(0.430)	(3.266)	(1.297)
Credit × Local	3.011	9.006	13.604***	-0.048	2.342	0.887
	(2.415)	(8.069)	(3.430)	(0.284)	(2.162)	(0.877)
Month × Local	0.443*	2.033*	1.692***	-0.028	0.052	-0.004
	(0.251)	(1.069)	(0.339)	(0.035)	(0.246)	(0.084)
GDP(log) × Month	-0.025***	0.006	-0.008	-0.003***	-0.003	-0.003**
	(0.008)	(0.010)	(0.006)	(0.001)	(0.002)	(0.001)
Population(log) × Month	0.021*	-0.020**	-0.004	0.003**	0.003*	0.003**
	(0.012)	(0.010)	(0.007)	(0.001)	(0.002)	(0.001)
Branch FE	YES	YES	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES	YES	YES
Observations	2,899	2,861	2,887	2,899	2,861	2,887
R-squared	0.257	0.084	0.171	0.067	-0.013	0.053
Number of branches	206	192	194	206	192	194

Table 8: Heterogeneity in LTV ratios

Note: This table reports the results of the following regression

$$Y_{it} = \alpha + \beta_1 Credit_i * Month_{it} + \beta_2 Credit_i * Month_{it} * Local_{it} \quad (19)$$
$$+ \beta_3 Local_{it} + \beta_4 Credit_i * Local_{it} + \beta_5 Month_{it} * Local_{it} \quad (20)$$
$$+ \gamma_{ym} + \delta_i + \eta X_{it} + \epsilon_{it} \quad (21)$$

$$W_{it} = \theta + \mu_1 Z_i * Month_{it} + \mu_2 Z_i * Month_{it} * Local_{it} \quad (22)$$
$$+ \mu_3 Z_i * Local_{it} + \gamma_{ym} + \delta_i + \eta X_{it} + \epsilon_{it} \quad (23)$$

This table reports the heterogeneous changes in LTV ratios among branches with different credit levels based on panel data regression. Y_{it} is the simple average and weighted average by loan amount of LTV ratios for each branch in every active month. $Credit_i$ is sub-index credit around the branch's opening time divided by 100. $Month_{it}$ is the relative month to the opening time of each branch. $Local_{it}$ is the percentage of local cars in each branch' s monthly loan contracts. W_{it} includes $Credit_i * Month_{it}$, $Credit_i * Month_{it} * Local_{it}$ and $Credit_i * Local_{it}$. Z_i is the instrument variable. In columns (2) and (5) Z_i is the logarithm of distance to Hangzhou and in columns (3) and (6) Z_i is the sub-index payment in 2015. X_{it} are control variables, including the logarithm of GDP and population times a relative month. δ_j and γ_{ym} denote branch fixed effects and year-month fixed effects, respectively, and ϵ_{it} represents the error term. Standard errors are adjusted for robustness and reported in parentheses. ***, **, * denote significance levels at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Simple average			Weighted average		
	OLS	IV1	IV2	OLS	IV1	IV2
Credit × Month	-0.009	-0.090***	-0.028***	-0.009	-0.091***	-0.028***
	(0.011)	(0.031)	(0.010)	(0.012)	(0.031)	(0.009)
Credit × Month × Local	0.011	0.093***	0.025**	0.010	0.093***	0.024**
	(0.012)	(0.033)	(0.011)	(0.013)	(0.032)	(0.010)
Local	0.224	1.334	-0.035	0.213	1.348*	-0.023
	(0.335)	(0.816)	(0.267)	(0.333)	(0.802)	(0.268)
Credit × Local	-0.125	-0.851	0.049	-0.110	-0.853	0.049
	(0.208)	(0.534)	(0.177)	(0.208)	(0.525)	(0.180)
Month × Local	-0.015	-0.140***	-0.037**	-0.014	-0.141***	-0.036**
	(0.019)	(0.051)	(0.017)	(0.020)	(0.049)	(0.016)
GDP(log) × Month	0.001***	0.002***	0.002***	0.001**	0.002***	0.002***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)
Population(log) × Month	-0.000	-0.001	-0.001***	-0.000	-0.001	-0.001***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Branch FE	YES	YES	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES	YES	YES
Observations	2,899	2,861	2,887	2,899	2,861	2,887
R-squared	0.290	0.156	0.251	0.341	0.181	0.289
Number of branches	206	192	194	206	192	194