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In the shadow of big tech lending

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ABSTRACT

We investigate the impact of Big Tech lending on non-bank traditional lenders, which have a more overlapping clientele with Big Tech lenders than traditional banks. Our empirical methodology exploits geographical differences in Big Tech penetration ratios and adopts the instrumental variable (IV) approach using the FinTech payment adoption ratio and the distance to the Big Tech's headquarter. We find that the competition from Big Tech worsens the performance of branches facing stronger Big Tech competition by reducing the number of borrowers and the amount of loans. Moreover, branches in cities highly penetrated by Big Tech lending tighten the lending standard by reducing loan-to-value (LTV) ratios, measured as the approved loan amount per unit collateral value, while keeping the average collateral requirement unchanged. Our findings are consistent with the cream-skimming hypothesis that Big Techs possess better screening technology and reduce the quality of borrowers applying for traditional loans. Our results document novel changes in and responses of the non-bank traditional lending business in the Big Tech era.

1. Introduction

Financial technology (FinTech) has disrupted traditional means of providing financial services (Goldstein, Jiang, & Karolyi, 2019). One important group of major FinTech lenders is large technology companies, dubbed "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, using loan-level data from a car equity loan company with national branches in China. Unlike banks, non-bank lenders do not take deposits, thus facing higher funding costs and finding their niche in serving a riskier clientele that may have been rejected by banks. Thus, these non-bank traditional lenders often serve borrowers with higher credit risks than those served by banks and therefore face more direct competition from Big Tech lending.

Our empirical methodology exploits geographical differences in the 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 each branch's opening month. We evaluate

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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 originate more loans in terms of the number of transactions and the total loan amount in 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 endogeneity; 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, we use two instrumental variables (IVs): the great- circle distance to Hangzhou city, the Big Tech's 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 reduces 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 Big Tech competition induces local branches to lower the collateral requirement (measured by the average price of collateral per loan), we do find a reduction in the total collateral values, corroborating our argument that branches facing more intense Big Tech competition experience a reduction in the number of loans originated.

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 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 "cream-skimming" in the loan market by Big Techs, which may use more advanced FinTech to screen borrowers and "cherry pick" from the shared application pools. We also find that the increase in the lending standards pays off: branches facing fiercer Big Tech competition do not experience higher default rates, indicating the success of risk-control measures through lower LTV ratios.

Our paper contributes to several strands of the 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 has been a burgeoning literature on Big Tech credit (Beck, Gambacorta, Huang, Li, & Qiu, 2022; Boissay, Ehlers, Gambacorta, & Shin, 2021; Boot, Hoffmann, Laeven, & Ratnovski, 2021; de la Mano & Padilla, 2018; Frost, Gambacorta, Huang, Shin, & Zbinden, 2019; Gambacorta, Huang, Li, Qiu, & Chen, 2022; Hau, Huang, Shan, & Sheng, 2019; Hu, 2022; Huang, Li, Qiu, & Yu, 2022; Padilla, 2020; Stulz, 2019). For instance, Gambacorta, Huang, et al. (2022) examines two advantages of Big Techs compared to traditional banks: better information and better enforcement of credit repayment. Gambacorta, Khalil, and Parigi (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) finds 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. Boot et al. (2021) also holds similar opinions that Big Tech firms appear to have an edge over banks in both information-related and communication-related functions, especially for retail banking, with may lead to vertical disintegration of financial value chains. Hau et al. (2019) shows that Big Tech credit expands the market by creating credit access for borrowers excluded from traditional bank credit, especially in places where traditional financial intermediation is undersupplied. 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 is the clientele of banks. An abundant literature has documented FinTech lenders' disruptive impact on traditional banks (Buchak, Hu, & Wei, 2021; Goldstein et al., 2019). Several papers also provide evidence that FinTech may complement traditional lending by targeting riskier borrowers and smaller-sized loans and through regulatory arbitrage (Buchak, Matvos, Piskorski, & Seru, 2018; Erel & Liebersohn, 2020; Tang, 2019). In addition, Beaumont, Tang, and Vansteenberghe (2022) finds that FinTech lenders may improve SMEs' credit access to banks by alleviating their collateral constraints, through their provision of unsecured lending. While previous studies 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 those faced by banks. As a result, their clientele is of higher risk 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 ratio, to contain default rates. Interestingly, the interest rates charged by 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 to not 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 context but is usually based on a combination of features that include the characteristics of the customer-lender interaction and the screening and monitoring technology (Berg, Fuster, & Puri, 2021). The main practice of FinTech lending business includes Big Tech lending, P2P lending, and the digital transformation of banks.

2.1.1. Big Tech lending

The Big Tech lending in China emerged through the "3–1-0" credit model created by Alibaba, which originates loans to online business owners relying on its e-commerce platform and ecosystem (Liu, Lu, & Xiong, 2022). The term "3–1-0" indicates that customers need only 3 min to apply for a loan online, and if approved, the funds reach the borrower's Alipay account within 1 s, with the whole process entailing no manual intervention. The scale of China's Big Tech credit industry ranks the first in the world. The top digital banks in China, such as WeBank and MYbank, issue millions or even tens of millions of loans every year, with the average nonperforming loan ratio remaining at 1%–2%, far lower than the nonperforming rate of SME loans of traditional commercial banks (Huang & Qiu, 2021).

2.1.2. P2P lending

The development of P2P lending in China began in 2007, and went through the phases of infancy, growth and prosperity, collapse and contraction, and finally 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 total 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 3433 in 2015. In December 2015, the regulatory authorities released rules for P2P lending for the first time,[1] and the number of online lending platforms began to decline. At the end of 2017, the total 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.[2] In December 2018, the regulatory authorities issued "Opinions on Classifying and Disposing of Online Lending Institutions and Risk Prevention", proposing that problematic P2P lending institutions be shuttered.[3] By the end of 2020, all P2P platforms had been closed (Shen & Wang, 2021).

2.1.3. 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 involves multiple dimensions, including managerial awareness 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 banks had launched their own online lending products by 2018. Since the entire process of lending must be completed on an online platform, a powerful and robust digital system must be developed. Thus, state-owned banks have been ahead of joint-stock banks in the development of online lending (Research Group of Institution of Digital Finance, 2019).

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 has often been insufficient prior to the rise of FinTech and Big Tech lending. These borrowers must obtain loans from other financial institutions, and micro-loan companies play an important role in serving these credit-constrained groups.

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 Micro-Loan Companies," which stipulates the nature, establishment, source, and use of funds and other related issues of micro-loan companies.[4] In 2020, the China Banking and Insurance Regulatory Commission issued the "Notice on Strengthening the Supervision and Management of Micro-Loan Companies," emphasizing the need to strengthen supervision and management and rectify the order of the microloan industry.[5] 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.

[1] http://www.gov.cn/xinwen/2015-12/29/content_5028669.htm

[2] https://news.stcn.com/sd/202012/t20201201_2583380.html

[3] This policy document is not publicly available on the official government website, but many media (including official media like Xinhua News) have reported the content of this document and regarded it as an important turning point in the regulating process of P2P industry in China. See, for instance, http:// www.xinhuanet.com/2021-01/28/c_1127033879.htm and https://finance.ifeng.com/c/7je4lLlAV3A

[4] http://www.gov.cn/gzdt/2008-05/08/content_965058.htm

[5] http://www.gov.cn/zhengce/zhengceku/2020-09/19/content_5544764.htm

2.3. The Car equity loan business

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: (1) the collateral vehicle must be parked in a specific garage and the borrower cannot use the vehicle before repayment; and (2) 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. Fig. 2 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 portion 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 a 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, a borrower only needs to decide on the amount to apply for, and the officer recommends standardized products for the borrower. Each loan product is standardized so that its interest rate, loan term, and loan payment schedule are 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. The borrower's choice of a loan product determines the interest rate, loan term, and loan payment schedule, as these contract terms are uniformly set for a product.

Notably, the customers of microloan companies are likely to be different from those of commercial banks but may have a large overlap with those of Big Tech companies. For example, since the examined microloan company used vehicles as collateral, the average application amount and approval amount for each loan are 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 MYBank and WeBank, the digital banks owned by Ant Financial and Tencent, respectively, the average loan amount granted to their customers of SME owners is approximately 270,000 yuan, which is much closer to traditional microloans in terms of loan size. While FinTech and Big Tech loans typically do not require collateral, their targeted borrowers are usually those who used to rely on non-bank lenders to obtain loans. FinTech reduces the value of soft information in lending and weakens the advantage of non-bank traditional lenders, which may lose their relatively high-quality clientele to Big Tech lenders.

3. Data and empirical methodology

3.1. Data sources

Our data come mainly from the car equity loan company described in Section 2 from September 2015 to November 2017.[6] The dataset contains six types of information: (1) loan application information including borrower ID, application date, and application loan amount; (2) loan contract characteristics, including the origination branch, loan approval date, approved loan amount, loan product type, maturity, monthly interest rate, and the method of repayment. LTV ratios refer to the ratio of the approved amount to the assessed price of the car and serve as an instrument used 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 brand, mileage, assessed value, and license number; and (6) origination branch characteristics, including the address and the loan manager in charge.

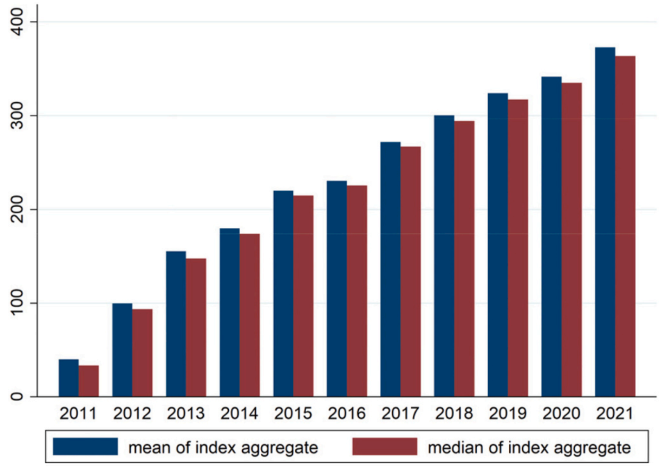
3.2. The analytical sample

3.2.1. Sample period

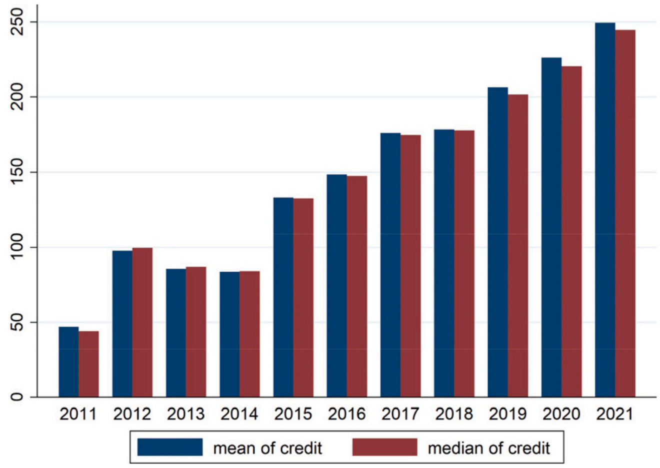
We obtain the entire lending history of the lender as of March 2019, which contains 216,647 observations since its first loan in May 2014. We only keep loan contracts from 206 branches that are active from April 2016 to November 2017 to exclude early-stage loans since the lender was exploring the business model. We drop 49,749 observations in and after December 2017 since the loan company started its digital transformation by adopting FinTech in loan origination.

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 branch. For the opening month of the branch, the variable *Month* equals one.

[6] In December 2017, the company started to adopt FinTech in its lending business. Chen, Dong, Jiayin, and Huang (2022) further investigates the impact of this FinTech adoption by the non-bank lender.



(a) Aggregate index



(b) Credit

Fig. 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.

3.2.2. Data cleaning

To exclude recording errors, we drop 19,961 outlier observations with assessed prices or approved amounts exceeding 200,000 or below 1000 and with no assessed prices. We exclude 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 these cities all exceed 30 days, making them outliers in terms of default rates. We also drop 216 observations from Jiyuan city, which is a county-level city, since our research focuses on prefecture-level cities and municipalities directly under the central government.

Our loan-level sample contains 146,565 loan-level observations between September 2015 and November 2017 in 206 branches around the nation. Our final sample is branch-month panel data that contains 47 branches in 2015, 122 branches in 2016, and 206 branches in 2017.

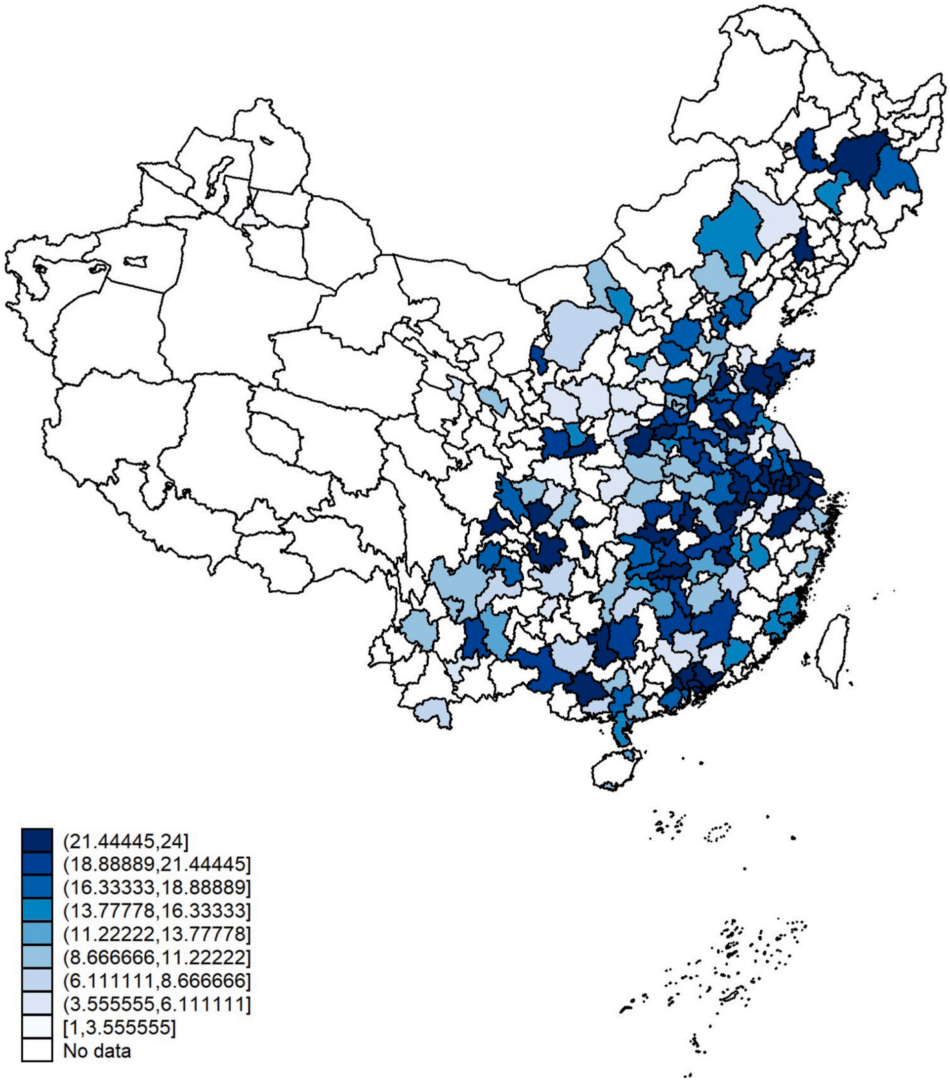


Fig. 2. Opening Time of Local Branches.
Note: The figure shows the opening month of the earliest branches at the prefecture-level. In this figure, 1 is November 2018, 2 is January 2018, 3 is December 2017, 4 is November 2017, 5 is October 2017, 6 is September 2017, 7 is August 2017, 8 is July 2017, 9 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.

3.3. Variable construction

3.3.1. LTV ratios

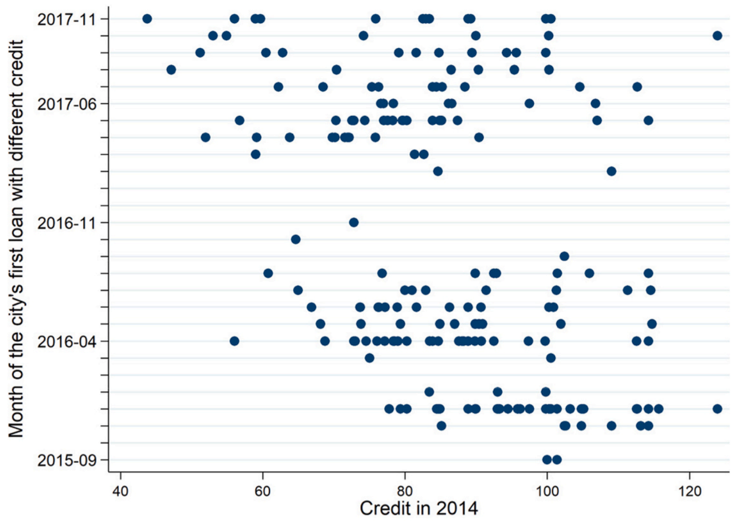
We calculate LTV ratios as the approved amount divided by the assessed price of collateral, which is the actual index used by the company to control risk. In the dataset, there is a variable named "reported proportion", which results from rounding the LTV ratios to one decimal place.

3.3.2. Default

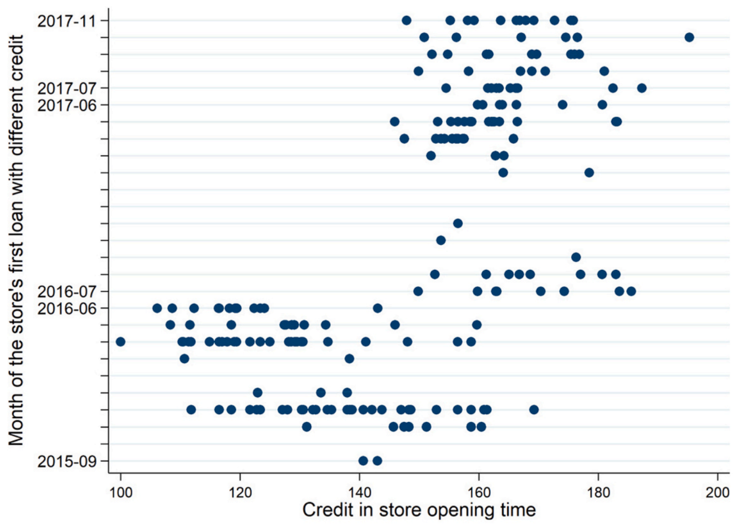
We define a variable *Default* to measure the ex post repayment situation. If the maximum number of default days exceeds 30 days, we define *Default* as one; otherwise, it is zero. We also run regressions using different default measures and find our results are robust.

3.3.3. Big Tech credit penetration

To identify the level of Big Tech credit business penetration in the city where the branch is open, we use the Big Tech credit index (*Credit*) from last year if the opening month falls between January and June; otherwise, we use the same year Big Tech credit index. For



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



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

Fig. 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.

instance, if the branch opened in March 2016, the Big Tech credit index 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.

We aggregate the loan-level data to branch-month level to calculate the number of loan contracts, the total amount of loans, and the total and average assessed price of collateral (all in logs). We also calculate the average LTV ratios and default rates for each branch-month unit, both in simple average method and using loan amount as weights.

3.3.4. Local vs. nonlocal borrowers

We use the license number of the collateral car to identify the registration city of the car plate. Local (nonlocal) borrowers are those with car registration city same as (different from) the location of the loan origination branch. We use the variable *Local* to measure branch-month proportion of local borrowers.

Table 1
Summary Statistics.

	N	Mean	Sd	min	max	p25	P50	p75
Month	2900	9.923	6.462	1	27	4	9	15
Number	2900	50.54	31.08	1	240	28	46	68
Number (log)	2900	3.673	0.835	0	5.481	3.332	3.829	4.220
Amount (in 10 thousand)	2900	300.32	183.49	2	1462	169.05	276.94	403.53
Amount (log)	2900	14.66	0.854	9.903	16.50	14.34	14.83	15.21
Price (in 10 thousand)	2900	407.96	252.81	3.1	2144.5	228.49	372.7	545.08
Price (log)	2900	14.97	0.851	10.34	16.88	14.64	15.13	15.51
Average price	2900	81,188	11,944	31,000	200,000	74,431	81,058	87,413
Average price (log)	2900	11.29	0.145	10.34	12.21	11.22	11.30	11.38
LTV ratios (simple average)	2900	0.747	0.0435	0.345	1	0.722	0.747	0.773
LTV ratios (weighted average)	2900	0.761	0.0405	0.345	1	0.739	0.761	0.784
Default rate	2900	0.151	0.211	0	1	0.0455	0.0882	0.156
Default rate (weighted average)	2900	0.150	0.214	0	1	0.0394	0.0846	0.158
Local	2899	0.876	0.148	0	1	0.833	0.920	0.976

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.

3.4. Descriptive analysis

Fig. 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. The opening month of the earliest branches at the prefecture-level, which is shown in Fig. 2, indicates that the company's business is in the process of expanding to the national scope. Panel A in Fig. 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 with the first batch of branches concentrated in cities with high credit and then gradually expanded to cities with low credit. Panel B in Fig. 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 the empirical analysis. Thus, by comparing the branches that opened during this period, we find that branches opening first have a high credit index.

In terms of geographic space, the distribution of branches of the car equity loan company we studied overlaps greatly with the distribution of the Big Tech credit penetration. Hence, the performance of the loan company is likely to be affected by the competition of Big Tech lending.

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 approximately 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 over 3 million, the total assessed price of collateral is over 4 million 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 the default rate are 0.151 and 0.150. The average ratio of local cars for each branch every month is 0.876, which means approximately 87.6% of loan contracts use local cars as collateral.

3.5. Empirical methodology

We investigate the impact of Big Tech lending on the non-bank traditional lender exploiting the geographic variation in Big Tech credit penetration ratios and car equity loan branch locations. The baseline panel regression is specified as follows:

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

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 Big Tech credit penetration index from the Peking University Digital Financial Inclusion Index of China (PKU-DFIIC) (Guo et al., 2020). We divide the original index by 100. $Month_{it}$ is the relative month to the opening time of each branch. For each branch, $Month_{it}$ equals one in the opening month. γ_{ym} and δ_j are year-month and branch fixed effects, respectively. X_{it} presents control variables for the located city, including the logarithm of GDP and population times a relative month.

Our OLS specification may over- or under-estimate the impact of Big Tech lending. For instance, since the Big Tech penetration index is at the city level, there may be omitted variables that affect both the level of Big Tech penetration and the performance of traditional loan origination; thus, endogeneity problems may arise. We use the instrument variable (IV) approach to address such problems. Our IV regression is specified below:

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

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

Table 2
Overall Business.

	(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	2900	2862	2888	2900	2862	2888
R-squared	0.259	0.151	0.228	0.250	0.135	0.215
Number of branches	206	192	194	206	192	194

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.

Table 3
Collateral Value.

	(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	2900	2862	2888	2900	2862	2888
R-squared	0.255	0.148	0.224	0.064	0.063	0.063
Number of branches	206	192	194	206	192	194

Note: This table reports the results of the following regression.

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

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

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.

Table 4
LTV ratios.

	(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	2900	2862	2888	2900	2862	2888
R-squared	0.277	0.260	0.252	0.325	0.300	0.289
Number of branches	206	192	194	206	192	194

Note: This table reports the results of the following regression.

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

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

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.

Table 5
Default Rate.

	(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	2900	2862	2888	2900	2862	2888
R-squared	0.885	0.878	0.884	0.869	0.862	0.868
Number of branches	206	192	194	206	192	194

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.

Table 6
Heterogeneity in Overall Business.

	(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	2899	2861	2887	2899	2861	2887
R-squared	0.262	0.080	0.180	0.250	0.083	0.161
Number of branches	206	192	194	206	192	194

Note: This table reports the results of the following regression.

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

$$W_{it} = \theta + \mu_1 Z_i{*}Month_{it} + \mu_2 Z_i{*}Month_{it}{*}Local_{it} + \mu_3 Z_i{*}Local_{it} + \gamma_{ym} + \delta_i + \eta X_{it} + \epsilon_{it} \tag{10}$$

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.

where Z_i denotes the instrument variable. Our first IV is the distance to the Big Tech's headquarter in Hangzhou city, which matters for the marketing and expansion of Big Tech's lending business. Since the Big Tech's headquarter location is predetermined, the geographical distance are thus not affected by local economic development and branch performance. Our second IV is the lagged Big Tech payment index in 2015, which measures the penetration ratios of Big Tech's digital payment technology. The Big Tech payment IV satisfies the relevance criterion because the information generated from digital payment is useful for predicting borrowers' default risks, and that the popularity of the digital payment platform benefits the usage of loan services on the same platform. Additionally, since we use the lagged value in 2015, which is prior to our sample period, the IV is also predetermined and thus satisfies the exclusion restriction criterion.

4. Main results

Previous studies have found that there is strong complementarity between Big Tech credit and traditional banks, but no obvious competition. This is because clientele served by Big Tech credit and traditional institutions have different credit standings and different scales of lending demands. Therefore, Big Tech credit has long been considered a complement to traditional loan services, which is mentioned in Section 1. However, the car equity loan company in our paper, which is a non-bank traditional lender, also serves small loan borrowers who find it difficult or complex to borrow from banks. From the perspective of serving clientele, Big Tech credit and non-bank traditional lenders overlap greatly. Thus, there is directly competition between them and with the emergence and popularization of Big Tech credit, the volume of business and risk taken by non-bank traditional lenders will be affected.

For the competition between Big Tech credit and non-bank traditional lenders, we have two main hypotheses: (1) competition will squeeze business of traditional mortgages, and (2) Big Tech credit provides more access to loans for borrowers, reducing the quality of borrowers who still choose traditional mortgages, which take on more risk.

Table 2 reports the impact of Big Tech credit on the non-bank traditional lender's overall performance, with the changes in the number of loans reported in Columns (1)–(3) and the total amount of loans reported in Columns (4)–(6). For the key variable, we focus

Table 7
Heterogeneity in Collateral Value.

	(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	2899	2861	2887	2899	2861	2887
R-squared	0.257	0.084	0.171	0.067	−0.013	0.053
Number of branches	206	192	194	206	192	194

Note: This table reports the results of the following regression.

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

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

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.

on –credit times the relative months –in the panel data OLS regression, the coefficient of the interaction term for number is 0.049 and that 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 endogeneity problem, the coefficient of the interaction term becomes significantly negative, which means if the branch is located in a city with a higher Big Tech penetration credit level, the number and total amount of loan contracts fall faster, indicating that in a location with higher Big Tech penetration, Big Tech credit is more competitive with non-bank traditional lenders and squeezes out more business.

The value of 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 average assessed price. The coefficient of the interaction term (*Credit* × *Month*) is significantly negative in the IV regressions for the total assessed price shown in Columns (2) and (3). The results indicate that if a 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 change in the number of loans, as shown in Table 2, 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, to some extent, showing that non-bank traditional lenders do not take the initiative to take higher risks because of competition.

For LTV ratios –the most important indicator to control risk in the company –the coefficient of the interaction term (*Credit* × *Month*) is −0.007 in Columns (2)–(3) for simple average LTV ratios and −0.008 in Columns (5)–(6) for weighted average, all significantly negative, as shown 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 because with higher sub-index credit, the competition from Big Tech companies is even fiercer and the borrowers that obtain 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.

Regarding 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 in both simple average and weighted average (weighted by loan amount),

Table 8
Heterogeneity in LTV ratios.

	(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	2899	2861	2887	2899	2861	2887
R-squared	0.290	0.156	0.251	0.341	0.181	0.289
Number of branches	206	192	194	206	192	194

Note: This table reports the results of the following regression.

$$Y_{it} = \alpha + \beta_1 Credit_i * Month_{it} + \beta_2 Credit_i * Month_{it} * Local_{it} + \beta_3 Local_{it} + \beta_4 Credit_i * Local_{it} + \beta_5 Month_{it} * Local_{it} + \gamma_{ym} + \delta_i + \eta X_{it} + \epsilon_{it} \tag{13}$$

$$W_{it} = \theta + \mu_1 Z_i * Month_{it} + \mu_2 Z_i * Month_{it} * Local_{it} + \mu_3 Z_i * Local_{it} + \gamma_{ym} + \delta_i + \eta X_{it} + \epsilon_{it} \tag{14}$$

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.

as shown in Table 5. This result also confirms the rationality of the difference in LTV ratios. Combining the results for LTV ratio and default rate, we can find that non-bank traditional lenders are forced to adjust their clientele in the face of competition from Big Tech credit, and use their own risk control channels - LTV ratio - to avoid large-scale default.

5. Further analysis

In the past, the geographical relationship between individuals and the branch plays a major role, and the branch can obtain more soft information about locals. For nonlocals, borrowing is relatively difficult because there is less soft information available for local branches and local branches are reluctant to lend to nonlocals to avoid unnecessary risk. If a branch lends money to more nonlocals, it means that the branch has stronger ability to collect soft information.

With the development of Fintech, Big Tech credit can solve the problem of nonlocals' difficulty in borrowing to a certain extent. Big Tech credit focuses mainly on credit loans, among which relationship loans occupy an important position. Big Tech credit can access information through borrowers' digital footprints, making up for the difficulty of obtaining loans due to geographical relationship. Thus, in the competition between Big Tech credit and local non-bank traditional lenders, Big Tech credit has more obvious advantages for nonlocals.

In cities with a high level of Big Tech penetration, Big Tech credit is more convenient and borrowers will disclose more information, so the advantage of branches in obtaining locals' soft information when lending is reduced. Thus, in the process of competing with Big Tech credit, the overall impact is relatively small if the branch itself is better at collecting soft information, which can be shown by higher proportion of nonlocals. Meanwhile, Big Tech credit has different degrees of influence on locals and nonlocals and nonlocals benefit more. When facing two channels for borrowing, more qualified nonlocals will choose Big Tech credit, while nonlocals who still borrow from non-bank traditional lenders are at higher risk than those part of locals. Therefore, with higher proportion of nonlocals, increased risk of the branch due to competition is larger.

We use the percentage of local cars for heterogeneity analysis and have two main hypotheses: when facing the competition with Big

Tech credit, if branches accept more local cars as loan collateral, (1) the overall competitive impact of Big Tech credit is greater, but (2) the branch will face less risk.

Table 6 shows the heterogeneity in the number and total amount of loans. If more local cars are used as collateral, which shows that the ability to collect soft information of this branch is relatively weak, the overall negative effect of Big Tech competition on the branch's business increases since the coefficient of the triple cross term (*Credit* × *Month* × *Local*) is significantly negative and the coefficient of the interaction term (*Credit* × *Month*) is significantly positive in Columns (3) and (6). In terms of the assessed price, the total price for each branch in a month is 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 yield the same conclusion as before: 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 and this situation is not impacted by the ratio between locals and nonlocals.

However, as reported in Table 8, if more local cars are used as collateral, the decline in the simple average and weighted average (weighted by loan amount) LTV ratios is smaller. Columns (2)–(3) and Columns (5)–(6) show that the coefficients of the triple cross term (*Credit* × *Month* × *Local*) is significantly positive, and coefficient of the interaction term (*Credit* × *Month*) is significantly negative. This is because Big Tech credit has a relatively weak role in replacing non-bank traditional lenders for locals. Even with Big Tech credit, locals who borrow from non-bank traditional lenders still have good credit. Thus, when facing the competition with Big Tech credit, branches with higher proportion of locals will face lower risk increases and their adjustments to the average LTV ratio are smaller.

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: 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 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, degrading 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 and non-bank financial institutions, is worth further investigation to obtain a comprehensive understanding of the opportunities and challenges in the Big Tech era.

Declaration of Competing Interest

None.

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