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Keywords: FinTech, algorithm, human biases, lending, quasi-experiments

JEL classification: G21, G41, G51

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Abstract

We investigate whether FinTech alleviates human biases in lending decisions under asymmetric information. Using proprietary data from a large auto equity loan company in China, we find that nonlocal borrowers obtain a smaller loan-to-value (LTV) ratio than their local counterparts, even after controlling for collateral value and other borrower characteristics. Using two quasi-experiments where the lender adopts different financial technologies, we find that replacing human decision-making with FinTech algorithms significantly reduces both the LTV ratio and default rate differences between local and nonlocal borrowers, mitigating lending biases against nonlocal borrowers. However, the introduction of FinTech credit scores to assist human decision-making through information provision has no impact. Our results thus demonstrate the potential of algorithms in correcting human biases and promoting financial inclusion.

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1 Introduction

The rise of financial technology (FinTech) has created a changing landscape in the lending business (Goldstein et al., 2019), with innovations such as big data and machine learning having the potential to promote inclusive finance. While a vast body of literature focuses on the impact of FinTech on overcoming collateral constraints through reducing asymmetric information, relatively few studies investigate other causes of financial frictions, particularly those caused by human biases.

This paper examines the impact of FinTech on reducing human biases in lending decisions. Complementing the research on FinTech's impact on racial, ethnic, and gender inequalities (for instance, Fuster et al., 2022), we investigate the differentiated treatment faced by nonlocal borrowers, or "geographical discrimination", which creates unnecessary financial constraints on human mobility. We find that the introduction of FinTech credit scores to assist human decision-making does not reduce the biases against nonlocal borrowers, who obtain a smaller loan-to-value (LTV) ratio at loan origination than local borrowers. In contrast, replacing human decision-making with FinTech algorithms reduces the LTV ratio differences between local and nonlocal borrowers without increasing their default rate differences, suggesting that the local-nonlocal differences are more likely to be taste discrimination than a lack of information.

Our proprietary loan-level data come from a car equity loan company with national branches in China. While a car is used as collateral for a loan, the borrower retains the use and control rights of the car. The company installs a GPS in the collateral car, which can be located and repossessed if the borrower defaults or the car surpasses a certain boundary. In this way, the lender ensures that the collateral car will remain within its reach. We define local borrowers as those who borrow from a branch in the same city as indicated by their car plate numbers. Although there are no driving restrictions based on license plates in most cities in China, we find that local borrowers receive higher LTV ratios, i.e., the fraction of the assessed car prices as approved loan amounts, even after controlling for the collateral car value and other loan and personal characteristics. However, this local-nonlocal difference does not necessarily indicate human biases in lending decision-making since nonlocal borrowers on average have higher default rates than local borrowers. Thus, the differentiated treatment of local and nonlocal borrowers could also be driven by the rationale to maximize risk-adjusted profits.

We exploit two quasi-natural experiments where the lender adopts two different FinTechs to identify the impact of FinTech on local-nonlocal differences. Specifically, the first quasi-experiment features the introduction of FinTech credit scores in December 2017 (*FinTech score event*), which enables loan officers in local branches to make decisions based on big data. The second quasi-experiment involves the introduction of a centralized algorithm based on machine learning technology in June 2018 (*FinTech algorithm event*), which largely replaces human judgment with an algorithm in making lending decisions. Our empirical methodology exploits the FinTech adoption shocks and borrower characteristics to run difference-in-differences (DID) regressions. We include branch and year-month fixed effects to control for time-invariant branch characteristics and time-variant factors that are common to local and nonlocal borrowers, respectively. Since the FinTech adoption experiments are conducted in a top-down manner by the headquarter, we argue that these shocks are exogenous to the pre-experiment lending behavior and borrower quality of a given local branch. Thus, we are able to interpret our within-branch coefficients as the causal impact of FinTech adoption.

Our regression results show that the type of FinTech matters for reducing human biases in lending decisions: introducing big data credit scores does not reduce the differences in LTV ratios between local and nonlocal borrowers, while replacing decentralized human decisions with a machine-learning-based algorithm is effective. Specifically, replacing human decision-making with FinTech algorithms significantly reduces both the LTV ratio and default rate differences between local and nonlocal borrowers, rejecting the hypothesis that the lower LTV ratios received by nonlocal borrowers are fully explained by the rational motive to contain default risks. In contrast, we find that the introduction of FinTech credit scores to assist human decision-making through information provision has no impact on mitigating lending biases against nonlocal borrowers. Our results are robust under alternative specifications, measurements of default rates, and sample constructions. Overall, our analysis indicates a lending bias against nonlocal borrowers that is not driven by the actual default risks and the impact of FinTech algorithms that replace human decision-making on reducing the biases and promoting financial inclusion.

Our paper contributes to several strands of literature.

First, our paper provides novel empirical evidence on how the introduction of FinTech helps to alleviate discrimination by traditional lenders, contributing to the burgeoning literature on how technology helps reduce human biases in decision-making. Several recent papers examine the role of robo-advising in reducing biases in individual lending. Prominently, D'Acunto et al. (2021) quantifies cultural biases in FinTech peer-to-peer lending compared to automated robo-advising lending. They find stereotypical discrimination based on demographics to be both pervasive and economically costly, and the results are more pronounced for lenders in regions with higher salience of cultural biases. Our paper uses a novel empirical setting of FinTech adoption by a traditional loan company to investigate identity-based discrimination and the role of algorithms in reducing the geographical biases of local loan officers.

Second, our paper indicates the different impacts of big data and machine-learning-based algorithms on financial decision-making, deepening the literature on the impact of big data, machine learning, and algorithms. Recent literature has shown how big data and alternative data complement traditional information in assessing borrowers' default risk by increasing the prediction accuracy of delinquency rates, especially for borrowers without credit history or official credit scores (Agarwal et al., 2019; Gambacorta et al., 2019; Berg et al., 2020;

Jiang et al., 2020; Huang et al., 2020). Several papers also examine the value of big data and digital footprints in combating the COVID-19 pandemic Xiao (2020). While the use of big data is widely regarded as beneficial, and the concerns mainly concentrate on privacy issues, research on the impact of machine learning generates rather mixed results. Kleinberg et al. (2015) maintain that machine learning has the potential to increase social welfare through improved prediction. Rossi and Utkus (2020) find that inexperienced investors and investors with biased trading behaviors (such as high cash holdings and trading volumes) would benefit more from algorithm-based robo-advising. However, Mullainathan and Obermeyer (2017) argues that machine learning may amplify existing errors in human judgment when applied to health care due to measurement issues in health data. Fuster et al. (2022) show that the introduction of machine learning in the U.S. mortgage market has distributional effects, where Black and Hispanic borrowers are disproportionately less likely to gain. Contributing novel empirical evidence to the discussion, our paper underscores that FinTech's impact largely depends on its role in the decision-making process. Technologies assisting human decision-making may have a limited impact on correcting biases, while those serving as a replacement effectively reduce discrimination.

Third, our paper adds novel evidence to the FinTech adoption literature by investigating the FinTech transformation of a traditional loan company. Previous research concentrates on the adoption of digital payment technologies (e.g., Gowrisankaran and Stavins, 2004; Dalton et al., 2018; Jack and Suri, 2014; Jiang et al., 2020) and often examines how exogenous shocks facilitate FinTech adoption; prominently, the 2016 demonetization in India (e.g., Chodorow-Reich et al., 2020; Crouzet et al., 2019), the COVID-19 pandemic (Fu and Mishra, 2022), and government interventions (Higgins, 2020). The adoption of FinTech payment also expands the financial access of households and firms, relaxing borrowing constraints faced by households (**?**Ghosh et al., 2022) and firms (especially small- and medium-sized firms, SMEs) (Dalton et al., 2018; Gambacorta et al., 2022; Beck et al., 2022) and sustaining their financial resilience (Jack et al., 2013; Jack and Suri, 2014; **?**). Other types of FinTech adoption, such as smartphone applications for personal financial management, increase the financial wellness of households by reducing financial fee payments and penalties (Carlin et al., 2017). Adding to previous research on FinTech adoption by households and firms, our paper investigates FinTech adoption by a traditional lender, with implications for the financial access of individual borrowers. To the extent that FinTech can potentially alleviate biases in lending, FinTech adoption by traditional lenders is beneficial to promoting inclusive finance.

Fourth, our paper expands the research scope of the literature on the relationship between FinTech and traditional financial institutions by examining the integration of FinTech into traditional lending. An abundant literature has documented the disruptive impact of standalone FinTech companies or startups on traditional banks, such as the competitive pressure brought by FinTech lenders (Buchak et al., 2018) and FinTech financial management (Buchak et al., 2021). Several papers also provide evidence that FinTech may complement traditional lending by targeting riskier borrowers and smaller-sized loans (Tang, 2019). While previous studies mainly discuss the relationship between FinTech firms and banks, our research focuses on nonbank financial institutions (NBFIs) in the FinTech era and examines the integration of FinTech and traditional lending. We exploit policy shocks where a traditional loan company makes its FinTech transition by introducing big data and machine learning into its business model. Our analysis demonstrates how traditional lenders respond to the changing landscape of FinTech and highlights FinTech's potential to transform the traditional lending business.

Fifth, our paper documents geography-based discrimination against nonlocal borrowers in lending practice, which enriches our understanding of decision-making biases in the financial industry. Previous literature on FinTech and inequalities primarily focuses on the impact of FinTech on racial, ethnic, and gender inequalities. Our analysis extends the research scope to inequalities based on social identity. Policies and restrictions based on geographical features (such as the *hukou* system in China) not only create barriers to labor factor mobility and reduce allocational efficiency but also generate stigma that carries over to other aspects, including the financial access of certain groups of people.

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 describes our data and presents our empirical methodology using the two quasi-experiments. Section 4 provides descriptive analysis on differences in nonlocal and local loans. In Section 5, we analyze the impact of the introduction of a FinTech credit score on human decision-making. In Section 6, we examine the impact of an FinTech algorithm in reducing biases against nonlocal borrowers. We discuss our findings and conclude the paper in Section 7.

2 Institutional Background

2.1 Non-Bank Financial Institutions in China

Lending institutions are generally classified into depository and nondepository financial institutions, depending on whether a financial institution absorbs public deposits. Banks are typical depository financial institutions worldwide.[1] In China, nondepository financial institutions include financial leasing companies, auto-financing companies, consumer finance companies, pawn shops, and microcredit companies.

While the banking industry plays a dominant role in providing credit in China, the availability of loans from the banking system is often insufficient for SMEs and low- to middle-income households, who have to obtain credit informally or from non-bank financial institutions (NBFIs). Microcredit companies play an important role in serving credit-constrained people. According to the PBOC, there were 6,453 microcredit companies nationwide, with

[1] In China, there are also other types of depository financial institutions, namely “credit cooperatives” and “finance companies”. These institutions are usually quasi-bank institutions or subsidiaries of banks, and their scale is much smaller.

a loan balance of 941.5 billion yuan in China as of the end of 2021.

Nonbank lenders differ from banks in many aspects, including funding sources, qualifications of customers, and regulatory requirements. Take microcredit companies for an example. Microcredit companies in China are prohibited from accepting public deposits, so their funding sources are relatively limited and expensive. As the higher funding costs correspond to a higher interest rate than banking institutions, the borrower pools of microcredit companies are usually riskier than those of banks. Additionally, microcredit companies are regulated differently from banks. In the Chinese regulatory framework, banks and some nondepository financial institutions, such as auto-financing companies and consumer finance companies, are regulated by the China Banking and Insurance Regulatory Commission (CBIRC), while microcredit companies are regulated by local governments. On the other hand, the compliance requirements and restrictions on a microcredit company, such as those regarding capital ratios, ownership structures, and leverage ratios, are considerably lower with those on banks.

2.2 The Auto Equity Loan Business

Originating auto equity loans is a typical business model for microcredit companies. An auto equity loan is a personal loan that are secured by borrowers' equity in vehicles and can be used for various purposes.[2] There are two types of business models of auto equity loan companies in China: One is that the collateral vehicle must be parked in a designated garage, and the borrower cannot use the vehicle before full repayment. The other business model is that borrowers are able to retain the use of their vehicles after the lenders install GPS to locate the vehicles. 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 productive assets for their business, so

[2] An auto equity loan differs from an auto loan though both use vehicles as collateral. The latter is analogous to a housing mortgage loan in that the borrower uses the money for the purchase of the collateral, while the loan purpose of an auto equity loan can be diverse.

the latter model is more desirable. However, for the lenders, the second model increases the risk of default.

The microcredit company we examined in this paper was founded based on the second lending model. This company launched its first microloan product in May 2015, and with the continuous expansion of its business, it gradually opened nearly 200 offline stores covering over 160 cities across China. Most of the company's funds came from P2P platforms, and a small part comes from banks, insurance companies, financial trusts, or other financial institutions. The borrowers were mainly SME owners and self-employed individuals who were not served by the traditional banking industry.

Note that in this microcredit company, the loan product is standardized in that within a loan product type, the interest rate, loan term, and loan payment schedules are uniformly set, regardless of the borrower characteristics. The interest rate of the loan product might be adjusted according to the market conditions but did not vary across different borrowers. There are nine choices of maturity, which are 1, 2, 3, 6, 9, 12, 18, 24 and 36 months. There were two types of loan payment schedules: even total payment or a balloon payment where borrowers pay the interest every month and repay all the principal when the loan was due.

In terms of post-loan management, the lenders would install GPS on the vehicle to locate it. If the car leaves a certain geographical range or if a loan default occurs, it will be repossessed by the loan company. In addition, borrowers are required to report to the microcredit company one day in advance if they want to drive out of the city. Otherwise, the company would also locate and repossess the collateral car. The repossession of collateral vehicles is physically achieved and sometimes involves violence, incurring a relatively high enforcement cost.[3] This may explain why loan companies, including FinTech companies,

[3] A new starter interrupter technology, which allows lenders to remotely disable the collateral vehicle of borrowers who are behind on their repayment, is in use in other countries. See, for instance, https://www.cbsnews.com/news/car-repossession-device-starter-interrupter-auto-dealer-car-credit-city/ and https://archive.nytimes.com/dealbook.nytimes.com/2014/09/24/miss-a-payment-good-luck-moving-that-car/.

prefer to control the loan amount instead of raising interest rates. In this case, controlling the amount of principal is more conducive to minimizing potential losses.

2.3 Quasi-Experiments on FinTech Adoption

The introduction of big data credit score. On December 1, 2017, the loan company started to incorporate in the offline loan decision process a credit score developed by a Big Tech company. This credit score was calculated based on big data including mobile payment, online consumption, online lending, social footprint, etc., on the Big Tech platform. The third-party big data score was used as an additional reference for the loan officers in local branches when they determine the LTV ratios for borrowers. In this sense, this FinTech adoption only changed the information set of humans making loan decisions.

The introduction of an algorithm-based risk control system. On June 1, 2018, the loan company moved further in its FinTech transformation by establishing an online centralized risk control system based on machine learning algorithms. After adopting the centralized system, the loan application form was also switched to online, and the borrower was required to authorize the collection of mobile information such as the installation and usage of mobile apps and communication records. The information collected by offline loan officers during the review and investigation process is also uploaded to the system through photographs or scanning. After the upload of information, the standardized system would calculate a benchmark LTV ratio using big data algorithms and return the benchmark to offline stores. Then, the loan officers could make adjustments based on other information they had that was not captured by the hard data to determine the final approved LTV ratio.

Figure1 illustrates the decision-making process of the microcredit company before and after its adoption of FinTech. When a borrower applied for a loan at an offline store, the officer would determine the loan amount based on the application information and the condition of the collateral vehicle. Specifically, the approved loan amount is the product of 1) the assessed value of the collateral vehicle by a third party and 2) the LTV ratio determined by the officer based on the applicant's information and historical records. A higher loan ratio corresponded to a lower borrower risk level. The Fintech score event mainly affects the information set of loan officers who are still responsible for the decision making, while the FinTech algorithm event leads to an upheaval in the decision-making process since the algorithm replaces human in approving loans.

The exogeneity of these two FinTech adoption events come from the fact that these two Fintech transitions were both company-wide decisions made by the headquarter, which were exogenous to local borrower conditions and offline loan officers' performance in a given branch. Furthermore, these FinTech adoption efforts are purely profit-maximizing, without particular considerations related to discrimination and inequality issues, such as closing the differences between locals and non-locals. Therefore, these two shocks provide us with two excellent quasi-experiment settings to identify FinTech's impact on human biases in lending decisions.

3 Data and Empirical Methodology

3.1 Data Sources

Our data mainly come from the car equity loan company described in Section 2. We obtain the company's full history of loans originated between July 2016 and December 2018. The dataset contains six types of information: (1) loan application information including the borrower ID, the application date, and the loan amount requested in the loan application; (2) loan contract characteristics including the origination store, loan approval date, approved loan amounts, maturities, monthly interest rates, and the method of repayment; (3) loan performance information including maximum default days; (4) borrower characteristics such as age, gender, education level, marital status, and monthly income; (5) car characteristics such as the brand, the mileage, assessed value, and license number; and (6) origination store characteristics including the address and the loan manager in charge.

3.2 The Analytical Sample

Sample periods. 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 34,698 observations in the early period (i.e., during or before June 2016) to exclude early-stage fluctuations when the lender was exploring the business model. We also drop 5,738 observations in 2019 to avoid the undermeasurement of default rates due to few available loan repayment dates as of March 2019. Our sample period spans between July 2016 and December 2018, which contains 176,211 observations.

Sample cities. China's administrative system is a five-tier hierarchy: the central government, provinces (including 4 municipality cities), prefecture-level cities, counties (including county-level cities), and townships. We adopt the commonly used definition of cities, which includes all municipalities and prefecture-level cities but not county-level cities. Our research thus focuses on loans originated by branches located in municipalities and prefecture-level cities in Mainland China. We drop 526 observations originated from branches in Jiyuan city, which is a county-level city. We also drop 66 observations without license plate numbers and those with license plate numbers that do not indicate the issuing city.

To exclude recording errors, we drop 14,503 outlier observations with assessed car prices or approved amounts exceeding 200,000 yuan or below 1,000 yuan and those without assessed car prices. We exclude from our sample 51 observations whose approved amount is more than the assessed price of the collateral. Our final sample contains 161,065 loan-level observations between July 2016 to December 2018 in 218 stores .

3.3 Variable Construction

Local and nonlocal borrowers. We define local cars as collateral cars with license plates issued by the same city as the location of the loan origination branch and nonlocal cars as those with license plates issued by a different city. Accordingly, we define (non)local borrowers as those who borrow against (non)local cars.

Loan-to-value (LTV) ratios. We use LTV ratios to refer to the approved loan amount divided by the assessed price of the collateral car, which in practice serves as an instrument determined by the loan company to control risk.

The default indicator. We use delinquency rates to measure the ex post repayment situation. For each loan observation, we have the number of delinquency days if a borrower ever defaults on payment. If there are multiple delinquencies by the same borrower, our data would display the largest number of delinquency days. We define a default indicator that equals one if the number of delinquency days exceeds 30 days and zero otherwise. We conduct sensitivity analysis by varying the default threshold (e.g., from 30 to 0 days) and find that our results are robust.

3.4 Summary Statistics

Panel A of Table 1 reports summary statistics of our main variables[4] during the full sample period between July 2016 and December 2018. We find that less than 15% loans use nonlocal cars as collateral. The mean LTV ratio and reported proportion are 0.751 and 0.755 in the full regression sample, which means that on average the loan amount is approximately 75% of the value of collateral. The average maturity is 11.94 months.

Panels B, C, and D decompose the sample period into three mutually exclusive periods

[4]We take natural logarithms of the assessed price of cars, requested loan amount, and approved amount to approximate a normal distribution. Since some borrowers report zero monthly income, we add one to the raw data on monthly income before taking logs. Our results are robust if we take logs on the original income data.

and report summary statistics during the corresponding time period: (1) before the introduction of the FinTech credit score, i.e., between July 2016 and November 2017; (2) after the introduction of the FinTech credit score and before the introduction of the FinTech algorithm, i.e., between December 2017 and May 2018; and (3) after the introduction of the FinTech algorithm, i.e., between June 2018 and December 2018, respectively. We find that with the expansion of the company's business, the proportion of long-term loans increases and the average maturity becomes longer, which are 9.369, 15.88 and 26.26 in three subperiods, respectively. The average default rates are 0.0903, 0.0886, 0.127 and 0.0422 in the four time periods, respectively. The means of the logarithms of the assessed price of cars are 11.16, 11.17, 11.13 and 11.11 in the four periods, respectively, which means assessed price of cars are about 70,263, 70,969, 68,186 and 66,836 on average.

Panel A of Table 2 reports summary statistics and t-test results for local and nonlocal borrowers in the full sample. We find significant differences between local and nonlocal borrowers in all of our main variables.Panels B, C, D of Table 2 report results for the three subperiods as specified in Table 1, respectively. From December 2017 to May 2018, there is no significant difference in maturity and monthly interest rate chosen by local and nonlocal borrowers. However, from June 2018 to December 2018, there is no significant difference in our main variables expect for the assessed car price.

3.5 Empirical Methodology

Our empirical strategy exploits the two quasi-experiments that are adopted sequentially by the car equity loan company as described in Section 2. We exploit two quasi-experiments of the lenders' FinTech adoption to identify the impact of human-algorithm interaction. For the first quasi-experiment—adoption of FinTech credit score in December 2017, we take the window period from July 2017 to May 2018 and treat December 2016 as a false quasi-experiment. For the second quasi-experiment –adoption of a FinTech algorithm in June

2018, we take window period from January 2018 to November 2018 and treat June 2017 as a false quasi-experiment.

We adopt DID and triple-differences (DDD) approaches to identify FinTech's impact on correcting human biases. The regression model is specified as the following:

$$Y_{ijt} = \alpha + \beta_1 Nonlocal_{ijt} + \beta_2 post_t * Nonlocal_{ijt} + \gamma_t + \delta_j + \eta X_{ijt} + \epsilon_{ijt} \tag{1}$$

where i indexes the borrower, j indexes the branch, and t indexes the year-month. Y_{ijt} are outcomes for each observation including the LTV ratio, assessed car price, and default situation. $Nonlocal_{ijt}$ indicates the use of local or nonlocal cars as collateral and equals one if the car has a nonlocal license. $post_t$ indicates the month after the introduction. For the first shock, $post_t$ equals one if the loan occurs during the period from December 2017 to May 2018. For the second shock, $post_t$ equals one if the loan occurs during the period from June 2018 to November 2018. γ_t and δ_j are year-month and branch fixed effects, respectively. X_{ijt} are control variables for borrower and loan characteristics, including the assessed car price (in logs), male, age, education background, marital status, purpose of loan usage, monthly income (in logs), loan repayment type, maturity, monthly interest rate, and loan types.

We add branch fixed effects to control for the influence of economic development and other factors in different locations of stores and add year-month fixed effects to eliminate systematic changes due to the passage of time. Furthermore, we use characteristics of borrowers and features of loan contracts as control variables to exclude the impact of individual factors.

We further use the loans extended in the previous year as a comparison group to difference out the impact of seasonal and company-wide time-invariant factors. The DDD regression model is specified as follows:

$$
\begin{aligned}
Y_{ijt} = \alpha + \beta_1 Nonlocal_{ijt} * post_t * TreatedYear_t + \beta_2 Nonlocal_{ijt} * post_t \quad (2)\\
+ \beta_3 Nonlocal_{ijt} * TreatedYear_t + \beta_4 post_t * TreatedYear_t \quad (3)\\
+ \beta_5 Nonlocal_{ijt} + \gamma_t + \delta_j + \eta X_{ijt} + \epsilon_{ijt} \quad (4)
\end{aligned}
$$

where $TreatedYear_t$ equals one if the month falls into the window period of the actual shocks and zero otherwise. For the first quasi-experiment, $post_t$ equals one if the loan occurs during the period from December 2017 to May 2018 or during the period from December 2016 to May 2017. For the second quasi-experiment, $post_t$ equals one if the loan occurs during the period from June 2018 to November 2018 or during the period from June 2017 to November 2017.

4 Descriptive Analysis: Nonlocal-Local Differences

4.1 Descriptive Analysis

Figure 2 shows the time trend of nonlocal-to-local ratios in loan origination between July 2016 and December 2018. Panel A shows that the nonlocal-to-local ratio in terms of the number of loans fluctuates between 0.12 and 0.2. The amount of loans also demonstrates similar patterns, as shown in Panel B, where the highest level is in July 2018 and the ratio varies between 0.12 and 0.22. There are 85% more loans using local cars as collateral.

Panel A of Figure 3 shows the average LTV ratio for local and nonlocal cars each month, indicating that using local cars obtain a larger LTV ratio on average. The average LTV ratio is between 0.65 and 0.8. Before 2018, it has a rising trend, and then it fluctuates down for both local and nonlocal cars. Before June 2018, there is a significant difference between local and nonlocal cars; however, the gap becomes clearly narrower since June 2018.

Panel B of Figure 3 plots the default rate for local and nonlocal cars each month, showing that a loan using a nonlocal car is more likely to default. Overall, the default rate has a downward trend and fluctuates between 0.05 and 0.2 since July 2016 and before August 2018. Between February 2017 to the end of 2017, the default rate rises continuously for both local and nonlocal cars and drops again in July 2018 for local cars and in April 2018 for nonlocal cars. The default rate of nonlocal cars is slightly higher than that of local cars.

Figure 4 shows the distribution of maturity and monthly interest rate. In general, the decisions of locals and nonlocals on maturity and monthly interest rate are with similar distribution. There are only 20 different values of monthly interest rate in the sample, consistent the business method of controlling risk through LTV ratio rather than monthly interest rate to minimize potential losses due to high enforcement costs.

We estimate a nonparametric event study model to quantify the changes in the company's lending behavior before and after the two FinTech adoption events. Table 3 presents our results. We find that the nonlocal ratio in numbers and the amount of loans rises after the introduction of the FinTech credit score but do not change after the introduction of the FinTech algorithm. As shown in Panel A, the introduction of FinTech credit score has no significant impact on loans extended to local and nonlocal borrowers. However, Panel B shows that the aoption of FinTech algorithm is effective in closing the nonlocal-local gap in borrowing. Columns (3) and (5) of Panel B indicate that local borrowers' LTV ratio declines by more than nonlocal borrowers after the adoption of FinTech algorithm. Given that local borrowers have higher LTV ratios than nonlocal borrowers in pre-FinTech-algorithm periods, the difference in the LTV ratio between local and nonlocal borrowers decreases. Moreover, we examine the ex post default rates in Columns (4) and (6) and find that nonlocal borrowers experience a larger decline in default rates than local borrowers. Since the pre-FinTech default rate is higher among nonlocal borrowers than among local ones, our results imply that the difference in default rates between local and nonlocal borrowers also become smaller after the FinTech adoption. That is, the FinTech algorithm reduces the differences in borrowing capacity between nonlocal and local borrowers without leading to an increase in nonlocal default rates.

To more precisely examine the local-nonlocal difference in the LTV ratio and probability of default, we conduct analysis using the following regression specification:

$$Y_{ijt} = \alpha + \beta Nonlocal_{ijt} + \gamma_t + \delta_j + \eta X_{ijt} + \epsilon_{ijt} \tag{5}$$

where i indexes the borrower, j indexes the branch, and t indexes the year-month. Y_{ijt} are outcomes for each observation including the LTV ratio and default situation. $Nonlocal_{ijt}$ indicates whether local or nonlocal cars are used as collateral and equals one if the collateral car has a nonlocal license. γ_t and δ_j are year-month and branch fixed effects, respectively. X_{ijt} are control variables for borrower and loan characteristics, including the assessed car price (in logs), male, age, education background, marital status, purpose of loan usage, monthly income (in logs), loan repayment type, maturity, monthly interest rate, and loan types.

Table 4 shows the overall difference in the LTV ratio and probability of default between loans extended to local and nonlocal borrowers. We can find that local borrowers receive a larger fraction of the assessed car price as the approved loan amounts (*i.e., LTV ratio*). However, local loans also have a lower probability of default than nonlocal loans. These results are robust after we control for the collateral value and other loan and personal characteristics. Thus, the local-nonlocal difference in the LTV ratio, at its face value, does not necessarily indicate discrimination.

5 The Impact of Introducing FinTech Scores

The first quasi-experiment is the introduction ofFinTech credit scores in December 2017, which provides big data-based information to assist human decision-making. We use the

DID regression specified in Equation (1) to examine the impact of FinTech information provision on the differences in LTV ratios and default probabilities between local and nonlocal borrowers.

Table 5 reports the regression results during the sample period between July 2017 and May 2018, i.e., the five-month window before and after the FinTech credit score quasi-experiment. We do not find significant changes in nonlocal-local differences after the introduction of FinTech credit scores, neither in terms of LTV ratios (Panel A) nor default rates (Panel B). As shown in Column (1), the coefficient of the interaction term is 0.001, which is not statistically significant and has little economic significance. We include year-month fixed effects in all columns. Our results are robust if we add branch fixed effects in Column (2), add controls in Column (3), and add both in Column (4). Figure 5 illustrates the corresponding pretrend analysis. We find that the differences in both LTV ratios and default rates between nonlocal and local borrowers are relatively stable compared to the benchmark month (i.e., one month prior to the quasi-experiment), supporting that nonlocal and local borrowers have parallel trends prior to the adoption of FinTech credit scores.

To further eliminate the impact of confounding variables such as seasonal factors and time-invariant company-specific characteristics, we adopt a DDD analysis framework by comparing our DID results to the previous year. That is, we treat December 2016 as a false experiment month and construct a false window period between July 2016 and May 2017. Table 6 presents the DDD results. For LTV ratio, the coefficients of the triple cross term is 0.004 and the interaction term of $Nonlocal_{ijt}$ and $post_t$ is -0.004 with control variables and branch fixed effect. For default rate, the coefficient of the triple cross term is 0.048 and the interaction term of $Nonlocal_{ijt}$ and $post_t$ is -0.059 with controls and branch fixed effect. We find similar results that the external information provided by the FinTech credit scores has a limited and insignificant impact on the gaps in LTV ratios and probabilities of default between nonlocal and local cars.

Our results show that the availability of additional information – FinTech credit scores based on borrowers' digital footprints and big data – has no impact on narrowing the differences between nonlocal and local borrowers in ex ante loan origination (measured by LTV ratios) and ex post repayment behaviors (measured by whether the borrower ever defaults on the loan). Thus, our findings do not support the hypothesis that local branches treat nonlocal borrowers differently from local borrowers due to more severe asymmetric information. Instead, our results lend more strength to the argument that human biases matter in lending decisions: loan officers at local branches may discriminate against qualified nonlocal borrowers by offering lower LTV ratios. Therefore, FinTech that assists human decision-making through providing additional information has limited influence on lending decisions, which are ultimately made by biased humans. We find direct evidence supporting this human biases argument in the next section.

6 The Impact of FinTech Algorithm

We use the second quasi-experiment of introducing a standardized risk control algorithm to examine the impact of replacing human decision-making with FinTech algorithms. Table 7 presents our DID results. We find that the introduction of the FinTech algorithm is effective in correcting human biases. As shown in Column (1) of Panel A, the coefficient of the interaction term is 0.042, meaning that the adoption of FinTech algorithms reduces the disadvantages faced by nonlocal borrowers in LTV ratios by 4.2 percentage points, which is also economically significant. The impact decreases to 4 and 2.6 percentage points if we add branch fixed effects and control variables in Columns (2) and (3), respectively, and to 2.3 percentage points if we add both in Column (4). Nevertheless, the results are still statistically significant and economically important.

Furthermore, we do not find a significant impact on the probability of default, as shown in Panel B of Table 7. The coefficient of interaction term is -0.158 without controls and branch fixed effect. Adding controls, branch fixed effect and both, the coefficient becomes -0.134, -0.055 and -0.044. Figure 6 shows the pretrend effects, which fit the parallel trends hypothesis for both panels. The FinTech algorithm alleviates the ex ante disadvantages faced by nonlocal borrows in LTV ratios without increasing their ex post default rates. These findings combined indicate that differentiated lending decisions appear more likely to be human biases against nonlocal borrowers, which could be corrected by introducing a machine-learning-based algorithm to make lending decisions.

We perform the same DDD analysis for the adoption of the FinTech algorithm to eliminate the impact of confounding variables such as seasonal factors and time-invariant company-specific characteristics. We treat June 2017 as a false quasi-experiment and construct a false window period between January 2017 and November 2017. Table 8 presents the DDD results. We find the same results as in the DID analysis. As shown in Column (1) of Panel A, the coefficient of the triple cross term is 0.067, the interaction term of $Nonlocal_{ijt}$ and $post_t$ is -0.026, and the interaction term of $Nonlocal_{ijt}$ and $TreatedYear_t$ is -0.024, showing that the adoption of FinTech algorithms reduces the disadvantages faced by nonlocal borrowers in LTV ratios by 4.3 percentage points. The influence decreases to 4.2 and 2.7 percentage points if we add branch fixed effects and control variables in Columns (2) and (3), respectively, and to 2.2 percentage points if we add both in Column (4). The results are both statistically significant and economically important. Moreover, there is still no significant effect on the probability of default, as shown in Panel B of Table 8. The coefficient of triple cross term is -0.086, -0.102, -0.005 and -0.009 in four columns, respectively.

These results are consistent with our hypothesis that loan officers at local branches discriminate against nonlocals, underscoring the human biases in lending decision prior to the FinTech algorithm adoption. After the adoption of the FinTech algorithm, the differences in LTV ratio between nonlocals and local borrowers decreases because the algorithm can make objective decisions based on the available information and is not affected by taste. Our findings on the nonlocal-local differences in default probabilities further affirms that a higher LTV ratio for nonlocal borrowers would not lead to an increase in their default rates.

One concern regarding our analysis above is that ex-ante loan origination may also influence ex post repayment behavior, thus contaminating our estimation of the FinTech's impact on default probabilities. Table 9 shows the results adding the LTV ratios as a control variable. We do not find supporting evidence. We find that FinTech adoption—whether in the form of additional information or machine-learning-based algorithm—does not have significant impact on the differences in default rate between nonlocal and local borrowers.

Thus far, we have modeled default by whether delinquency exceeds 30 days, which is a relatively loose criterion. As robustness analysis, we use a stricter criterion of whether there are positive days of delinquency. If there is at least one day of delinquency, we treat this as a default. Table 10 presents the results after changing the default threshold. We find our main results are robust: nonlocals are more likely to default and both FinTech adoption do not affect the gap in default rates between nonlocal and local borrowers.

Another concern is that during 2017-2018, some branches closed or were not active in the market. To refine the sample of branches, we use branches active no less than 12 months during 2017-2018 for further tests. Table 11 shows the results for the effect of FinTech algorithms on the LTV ratio. Panel A presents the DID results and in Column (1), the coefficient of the interaction term is 0.041, meaning that the adoption of FinTech algorithms reduces the disadvantages faced by nonlocal borrowers in LTV ratios by 4.1 percentage points, which is similar to the previous coefficient in Table 7. The impact decreases to 4 and 2.6 percentage points if we add branch fixed effects and control variables in Columns (2) and (3), respectively, and to 2.3 percentage points if we add both in Column (4). The coefficients and significance levels are the same as the previous results in Table 7. The results of the DDD analysis are shown in Panel B, and we also find the same robust results as before.

7 Conclusion

We provide novel evidence that FinTech can reduce biases in lending. Using proprietary data from a car-backed loan company with national branches in China, our results show that loan officers tend to approve a larger fraction of the assessed collateral prices as loans to local borrowers, implying geographical discrimination against nonlocal borrowers since both types of borrowers do not exhibit significantly different default rates. Quasi-experiments on the lender's FinTech adoption show that the type of FinTech matters in the effectiveness of reducing geographical discrimination: the introduction of big data credit scores as an informational tool does not reduce bias, while a machine-learning-based algorithm is effectie by largely replacing human decisions. Our results document a novel channel through which FinTech expands financial access and promotes financial inclusion.

References

Agarwal, Sumit, Shashwat Alok, Pulak Ghosh, and Sudip Gupta, "Financial Inclusion and Alternate Credit Scoring: Role of Big Data and Machine Learning in Fintech," *SSRN working paper*, 2019.

Beck, Thorsten, Leonardo Gambacorta, Yiping Huang, Zhenhua Li, and Han Qiu, "Big Techs, QR Code Payments and Financial Inclusion," *SSRN working paper*, 2022.

Berg, Tobias, Valentin Burg, Ana GomboviÄ , and Manju Puri, "On the Rise of FinTechs: Credit Scoring Using Digital Footprints," *The Review of Financial Studies*, 2020, *33* (7), 2845–2897.

Buchak, Greg, Gregor Matvos, Tomasz Piskorski, and Amit Seru, "Fintech, regulatory arbitrage, and the rise of shadow banks," *Journal of Financial Economics*, 2018, *130* (3), 453–483.

_ , Jiayin Hu, and Shang-Jin Wei, "FinTech as a Financial Liberator," *NBER working paper*, 2021.

Carlin, Bruce, Arna Olafsson, and Michaela Pagel, "FinTech Adoption Across Generations: Financial Fitness in the Information Age," *NBER working paper*, 2017.

Chodorow-Reich, Gabriel, Gita Gopinath, Prachi Mishra, and Abhinav Narayanan, "Cash and the Economy: Evidence from Indiaâ s Demonetization," *The Quarterly Journal of Economics*, 2020, *135* (1), 57–103.

Crouzet, N., Apoorv Gupta, and F. Mezzanotti, "Shocks and Technology Adoption: Evidence from Electronic Payment Systems," 2019.

D'Acunto, Francesco, Pulak Ghosh, Rajiv Jain, and Alberto G. Rossi, "How Costly are Cultural Biases? Evidence from FinTech," *SSRN working paper*, 2021.

Dalton, Patricio S., Haki Pamuk, Ravindra Ramrattan, Daan van Soest, and Burak Uras, "Payment Technology Adoption and Finance: A Randomized-Controlled-Trial with SMEs," *SSRN working paper*, 2018.

Fu, Jonathan and Mrinal Mishra, "Fintech in the time of COVID-19: Technological adoption during crises," *Journal of Financial Intermediation*, 2022, *50*, 100945.

Fuster, Andreas, Paul Goldsmith-Pinkham, Tarun Ramadorai, and Ansgar Walther, "Predictably Unequal? The Effects of Machine Learning on Credit Markets," *The Journal of Finance*, 2022, *77* (1).

Gambacorta, Leonardo, Yiping Huang, Han Qiu, and Jingyi Wang, "How Do Machine Learning and Non-Traditional Data Affect Credit Scoring? New Evidence from a Chinese Fintech Firm," *SSRN working paper*, 2019.

_ , _ , Zhenhua Li, Han Qiu, and Shu Chen, "Data versus Collateral," *Review of Finance*, 2022.

Ghosh, Pulak, Boris Vallee, and Yao Zeng, "FinTech Lending and Cashless Payments," *SSRN working paper*, 2022.

Goldstein, Itay, Wei Jiang, and G Andrew Karolyi, "To FinTech and beyond," *The Review of Financial Studies*, 2019, *32* (5), 1647–1661.

Gowrisankaran, Gautam and Joanna Stavins, "Network Externalities and Technology Adoption: Lessons from Electronic Payments," *The RAND Journal of Economics*, 2004, *35* (2), 260–276.

Higgins, Sean, "Financial Technology Adoption," *Working paper*, 2020.

Huang, Yiping, Longmei Zhang, Zhenhua Li, Han Qiu, Tao Sun, and Xue Wang, "Fintech Credit Risk Assessment for SMEs: Evidence from China," *IMF working paper*, 2020.

Jack, William, Adam Ray, and Tavneet Suri, "Transaction Networks: Evidence from Mobile Money in Kenya," *American Economic Review*, 2013, *103* (3), 356–361.

_ **and Tavneet Suri**, "Risk Sharing and Transactions Costs: Evidence from Kenya's Mobile Money Revolution," *American Economic Review*, 2014, *104* (1), 183–223.

Jiang, Jinglin, Li Liao, Xi Lu, Zhengwei Wang, and Hongyu Xiang, "Deciphering Big Data in Consumer Credit Evaluation," *SSRN working paper*, 2020.

Kleinberg, Jon, Jens Ludwig, Sendhil Mullainathan, and Ziad Obermeyer, "Prediction policy problems," *American Economic Review*, 2015, *105* (5), 491–95.

Mullainathan, Sendhil and Ziad Obermeyer, "Does machine learning automate moral hazard and error?," *American Economic Review*, 2017, *107* (5), 476–80.

Rossi, Alberto G and Stephen P Utkus, "Who benefits from robo-advising? Evidence from machine learning," *Evidence from Machine Learning (March 10, 2020)*, 2020.

Tang, Huan, "Peer-to-peer lenders versus banks: substitutes or complements?," *The Review of Financial Studies*, 2019, *32* (5), 1900–1938.

Xiao, Kairong, "The Value of Big Data in a Pandemic," *SSRN working paper*, 2020.

Figure 1: The Loan Approval Process of the Car Equity Loan Company

Note: This figure presents the loan approval process of the car equity loan company. Each loan product was standardized, with its interest rate, loan term, and loan payment schedules uniformly set. The interest rate of the loan product might be adjusted according to the market conditions but didn't vary across different borrowers. The blue and orange boxes mark the two FinTech transitions in our paper respectively.

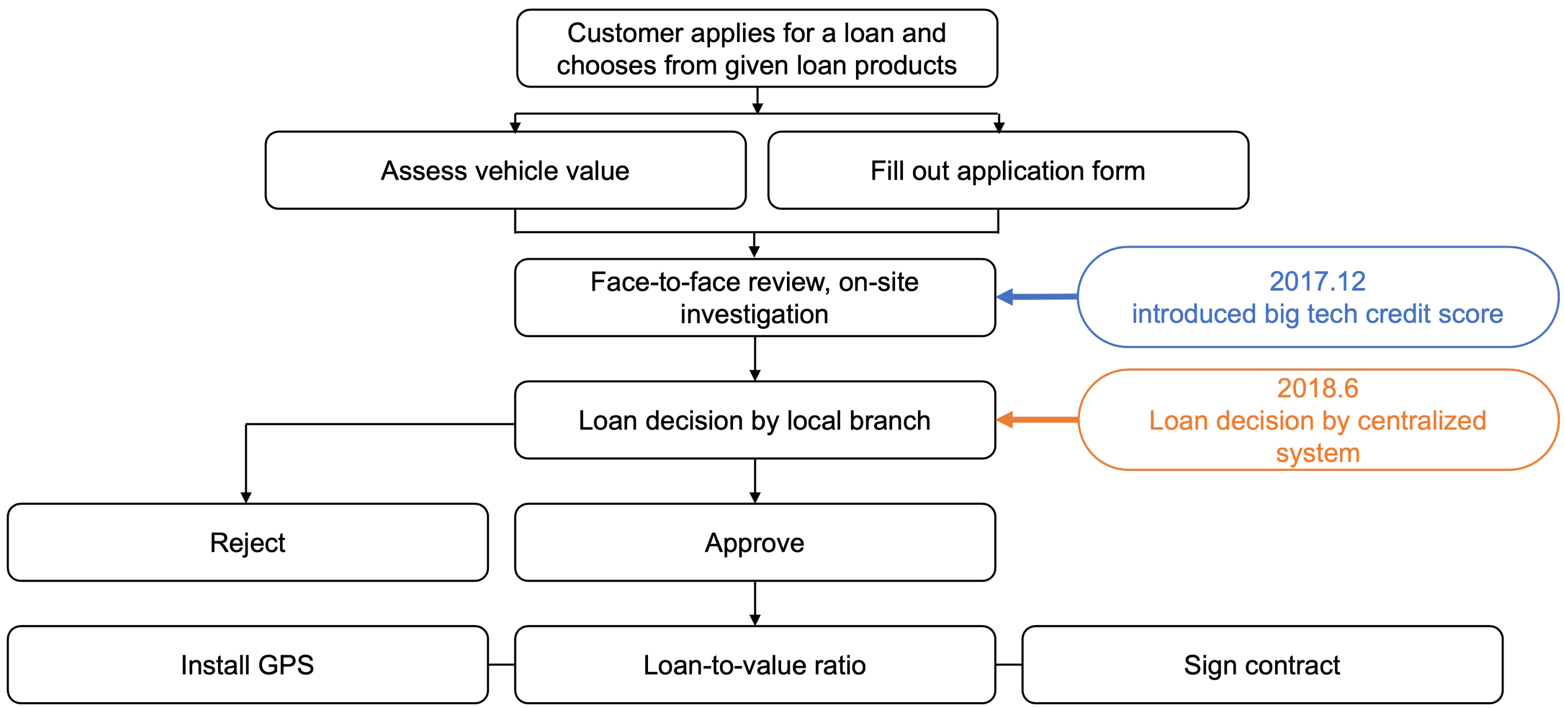
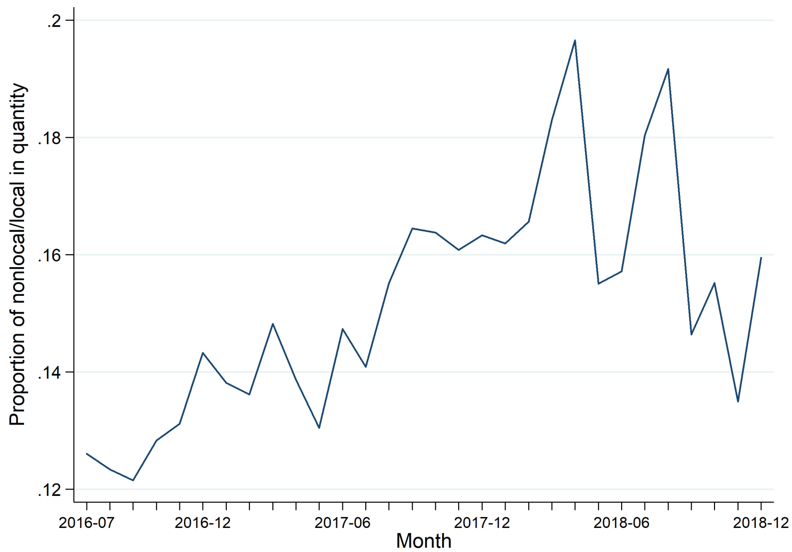
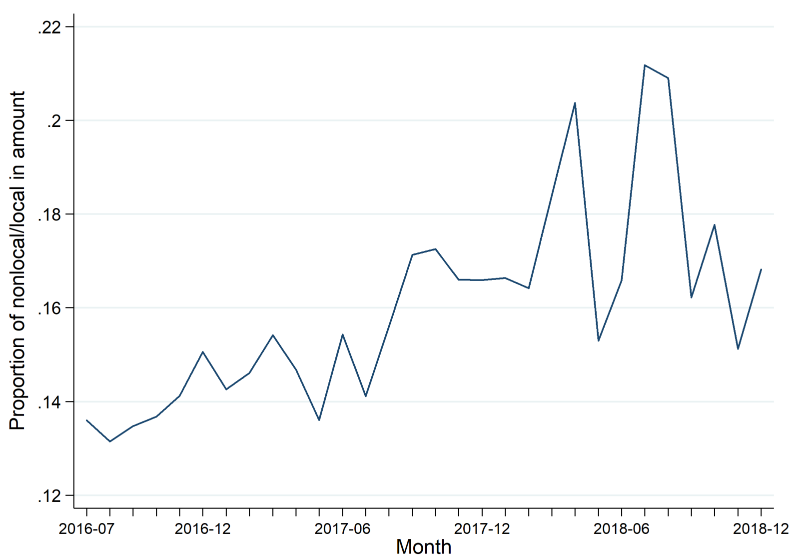


Figure 2: Time Trends of Nonlocal-Local Ratios in Car Equity Loans

Note: This figure plots the proportion of number and amount between nonlocal and local. Panel A plots the proportion of number of loans each month and panel B shows the proportion of total amount of loans each month.



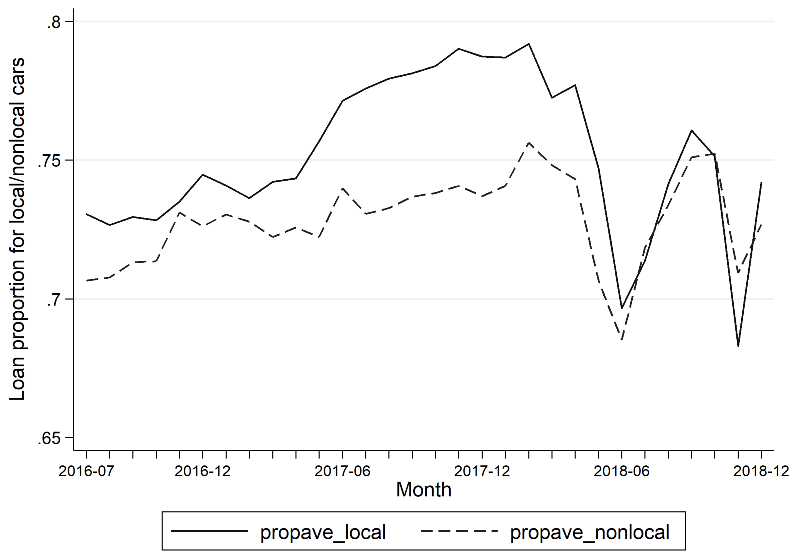
(a) Nonlocal-Local Ratios: Number of Loans



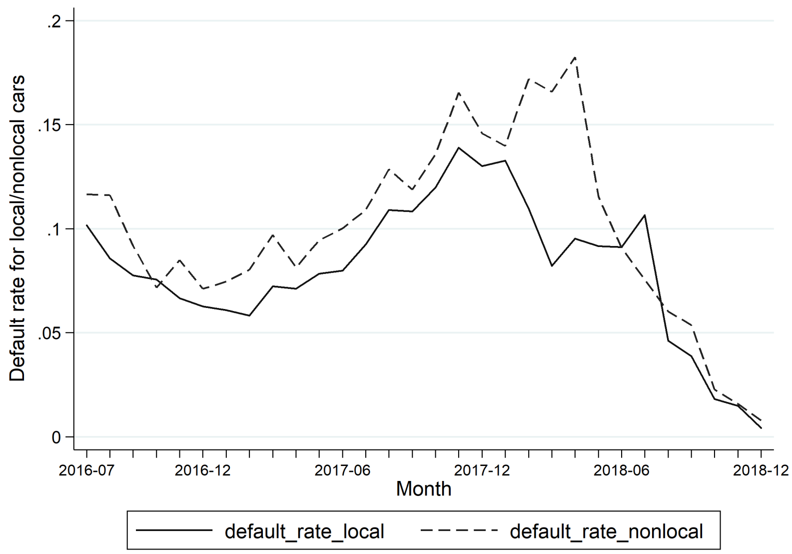
(b) Nonlocal-Local Ratios: Amount of Loans

Figure 3: Average Loan Proportion and Default Rate for Local and Nonlocal Loans

Note: This figure plots average LTV ratio and default rate for loans extended to local and nonlocal borrowers, respectively. Panel A plots average LTV ratio each month and panel B shows the default rate each month nationwide. The solid lines represent local loans and the dashed lines refer to nonlocal loans.



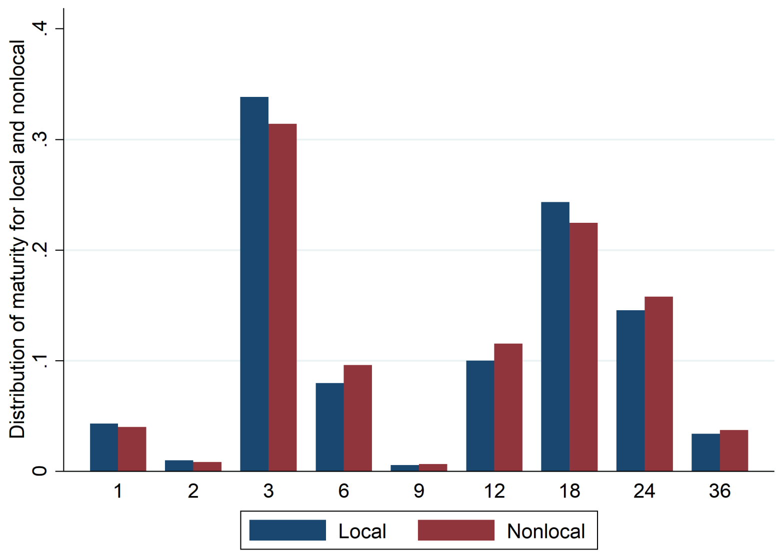
(a) Average LTV ratio



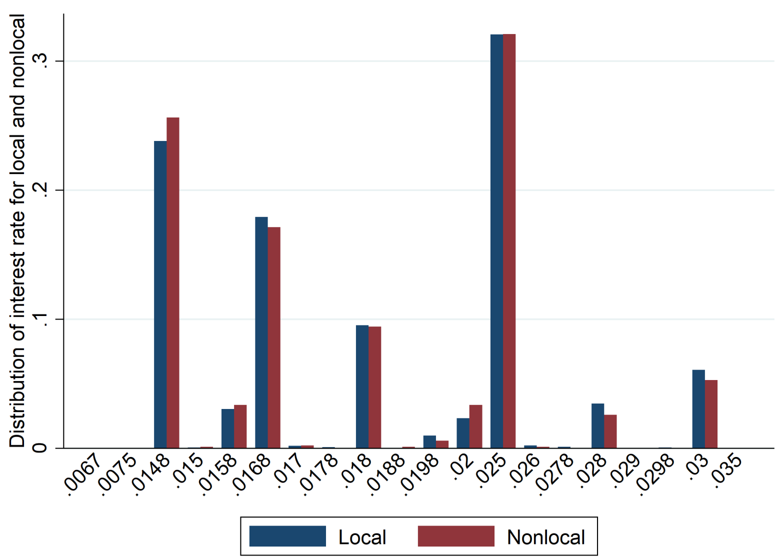
(b) Default rate

Figure 4: Distribution of Maturity and Monthly Interest Rate for Local and Nonlocal

Note: This figure plots the distribution of maturity and monthly interest rates chosen by local and nonlocal respectively. Panel A shows the distribution of loan maturity in which the blue bars represent the maturity chosen by local and the red bars refer to that chosen by nonlocal. Panel B shows the distribution of monthly interest rate in which the blue bars represent the monthly interest rate chosen by local and the red bars refer to that chosen by nonlocal.



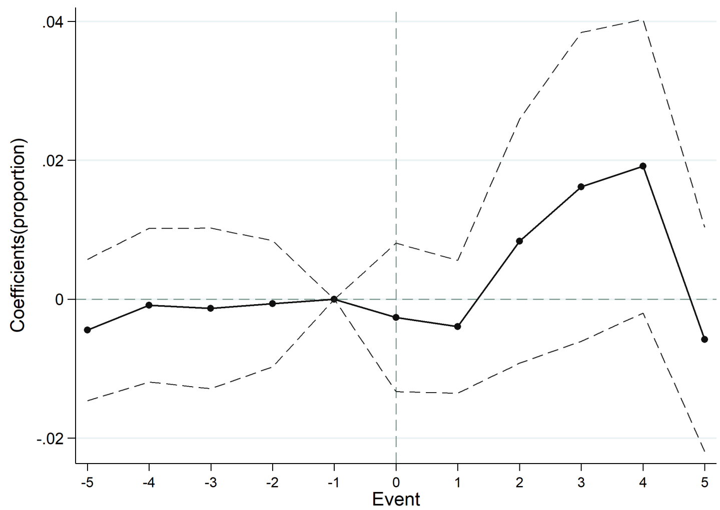
(a) Maturity



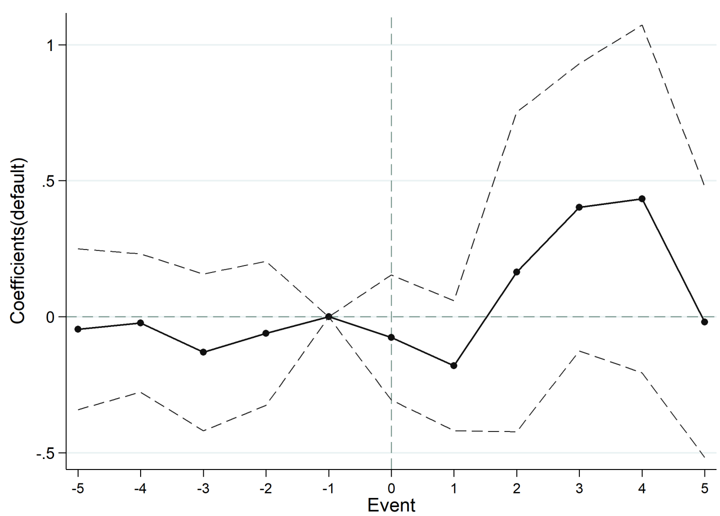
(b) Monthly interest rate

Figure 5: Pre-trend Analysis: The FinTech Score Shock

Note: This figure plots the difference in LTV ratio and probability of default between loans extended to local and nonlocal borrowers in 11 months intervals around the date of introducing the FinTech credit score. Panel A plots the difference in LTV ratio and panel B plots the difference in probability of default based on logit regression. The solid lines represent actual coefficients and the dashed lines are upper and lower bounds of confidence intervals. -5 on horizontal axis is July 2017, 5 is May 2017 and each label in turn represents a month. The vertical dashed line indicates the month of the introduction –December 2017.



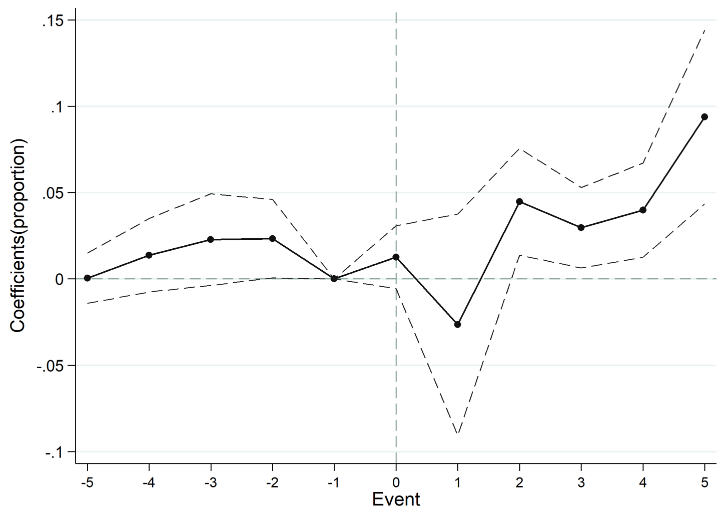
(a) The LTV Ratio



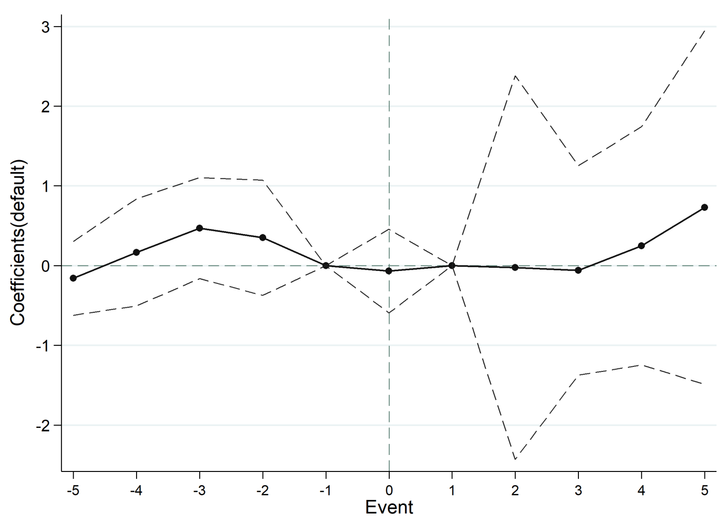
(b) The Probability of Default

Figure 6: Pre-trend Analysis: The FinTech Algorithm Shock

Note: This figure plots the difference in LTV ratio and probability of default between local and nonlocal borrowers in 11 months intervals around the date of introducing a FinTech algorithm. Panel A plots the difference in LTV ratio and panel B plots the difference in probability of default based on logit regression. For post 1, due to the small sample size of July 2018, it is dropped in the logit regression with month and store fixed effect, thus the point and confidence interval equal to zero. The solid lines represent actual coefficients and the dashed lines are upper and lower bounds of confidence intervals. -5 on horizontal axis is January 2018, 5 is November 2018 and each label in turn represents a month. The vertical dashed line indicates the month of the introduction –June 2018.



(a) The LTV Ratio



(b) The Probability of Default

Table 1: Summary Statistics

Note: This table reports summary statistics of the regression sample. The sample contains 161,065 loans from July 2016 to December 2018 in 218 stores around whole country. Panel A shows the summary statistics for the whole sample, panel B shows the situation before the introduction of FinTech credit score - from July 2016 to November 2017, panel C shows the situation after the introduction of FinTech credit score and before the introduction of FinTech Algorithm - from December 2017 to May 2018 and panel D shows the situation after the introduction of FinTech Algorithm - from June 2018 to December 2018.

	N	Mean	Sd	p5	p25	p50	p75	p95
Panel A: Full sample								
Price(log)	161,065	11.16	0.498	10.32	10.78	11.16	11.51	11.97
Reported proportion	161,065	0.755	0.134	0.500	0.700	0.800	0.800	0.900
LTV ratio	161,065	0.751	0.132	0.476	0.723	0.797	0.800	0.900
Maturity	161,065	11.94	9.274	2	3	12	18	24
Monthly interest rate	161,065	0.0203	0.00506	0.0148	0.0158	0.0180	0.0250	0.0300
Default	161,065	0.0903	0.287	0	0	0	0	1
Nonlocal	161,065	0.127	0.333	0	0	0	0	1
Panel B: Sample from July 2016 to November 2017								
Price(log)	121,005	11.17	0.498	10.33	10.80	11.16	11.54	11.98
Reported proportion	121,005	0.754	0.129	0.500	0.700	0.800	0.800	0.900
LTV ratio	121,005	0.750	0.127	0.487	0.733	0.796	0.800	0.900
Maturity	121,005	9.369	7.173	2	3	6	18	18
Monthly interest rate	121,005	0.0213	0.00504	0.0148	0.0168	0.0200	0.0250	0.0300
Default	121,005	0.0886	0.284	0	0	0	0	1
Nonlocal	121,005	0.124	0.329	0	0	0	0	1
Panel C: Sample from December 2017 to May 2018								
Price(log)	25,248	11.13	0.498	10.33	10.74	11.13	11.51	11.95
Reported proportion	25,248	0.779	0.137	0.500	0.800	0.800	0.900	0.900
LTV ratio	25,248	0.776	0.135	0.491	0.752	0.800	0.892	0.900
Maturity	25,248	15.88	9.605	2	6	18	24	24
Monthly interest rate	25,248	0.0180	0.00456	0.0148	0.0148	0.0148	0.0250	0.0250
Default	25,248	0.127	0.332	0	0	0	0	1
Nonlocal	25,248	0.141	0.348	0	0	0	0	1
Panel D: Sample from June 2018 to December 2018								
Price(log)	14,812	11.11	0.494	10.31	10.72	11.10	11.47	11.95
Reported proportion	14,812	0.721	0.159	0.400	0.700	0.800	0.800	0.900
LTV ratio	14,812	0.721	0.156	0.372	0.669	0.757	0.824	0.900
Maturity	14,812	26.26	8.499	6	24	24	36	36
Monthly interest rate	14,812	0.0166	0.00228	0.0148	0.0148	0.0168	0.0168	0.0168
Default	14,812	0.0422	0.201	0	0	0	0	0
Nonlocal	14,812	0.133	0.339	0	0	0	0	1

Table 2: Summary Statistics for Local and Nonlocal

Note: This table reports summary statistics of the regression sample for loans extended to local and nonlocal borrowers, respectively. The sample contains 140,553 loans for local and 20,512 loans for nonlocal from July 2016 to December 2018 in 218 stores around whole country. Panel A shows the summary statistics for the whole sample, panel B shows the situation before the introduction of FinTech credit score - from July 2016 to November 2017, panel C shows the situation after the introduction of FinTech credit score and before the introduction of FinTech Algorithm - from December 2017 to May 2018 and panel D shows the situation after the introduction of FinTech Algorithm - from June 2018 to December 2018. ***, **, * denote significance levels at 1%, 5%, and 10%, respectively.

	Local				Nonlocal				t-test	
	N	Mean	Sd	p50	N	Mean	Sd	p50	Sig.	p-value
Panel A: Full sample										
Price(log)	140,553	11.14	0.501	11.16	20,512	11.24	0.467	11.24	***	0.0000
Reported proportion	140,553	0.758	0.134	0.800	20,512	0.732	0.127	0.800	***	0.0000
LTV ratio	140,553	0.755	0.132	0.798	20,512	0.728	0.125	0.792	***	0.0000
Maturity	140,553	11.91	9.267	12	20,512	12.19	9.320	12	***	0.0001
Monthly interest rate	140,553	0.0204	0.00507	0.0180	20,512	0.0201	0.00497	0.0180	***	0.0000
Default	140,553	0.0880	0.283	0	20,512	0.106	0.307	0	***	0.0000
Panel B: Sample from July 2016 to November 2017										
Price(log)	106,018	11.16	0.500	11.16	14,987	11.26	0.469	11.26	***	0.0000
Reported proportion	106,018	0.757	0.129	0.800	14,987	0.732	0.126	0.800	***	0.0000
LTV ratio	106,018	0.753	0.127	0.797	14,987	0.727	0.124	0.792	***	0.0000
Maturity	106,018	9.363	7.186	6	14,987	9.415	7.075	6		0.4061
Monthly interest rate	106,018	0.0213	0.00505	0.0200	14,987	0.0211	0.00497	0.0200	***	0.0000
Default	106,018	0.0864	0.281	0	14,987	0.104	0.306	0	***	0.0000
Panel C: Sample from December 2017 to May 2018										
Price(log)	21,691	11.11	0.502	11.11	3,557	11.21	0.464	11.23	***	0.0000
Reported proportion	21,691	0.786	0.138	0.800	3,557	0.741	0.123	0.800	***	0.0000
LTV ratio	21,691	0.783	0.136	0.800	3,557	0.738	0.121	0.795	***	0.0000
Maturity	21,691	15.87	9.624	18	3,557	15.99	9.487	18		0.4567
Monthly interest rate	21,691	0.0180	0.00457	0.0148	3,557	0.0180	0.00453	0.0148		0.6447
Default	21,691	0.124	0.329	0	3,557	0.144	0.351	0	***	0.0006
Panel D: Sample from June 2018 to December 2018										
Price(log)	12,844	11.10	0.499	11.08	1,968	11.21	0.450	11.20	***	0.0000
Reported proportion	12,844	0.721	0.162	0.800	1,968	0.718	0.135	0.700		0.4029
LTV ratio	12,844	0.721	0.160	0.760	1,968	0.718	0.133	0.743		0.4563
Maturity	12,844	26.23	8.482	24	1,968	26.42	8.609	24		0.3475
Monthly interest rate	12,844	0.0166	0.00229	0.0168	1,968	0.0166	0.00221	0.0168		0.9585
Default	12,844	0.0417	0.200	0	1,968	0.0452	0.208	0		0.4731

Table 3: Changes Before and After Two FinTech Adoption Shocks

Note: This table reports the changes before and after two shocks in the business period of the company. The dependent variable is nonlocal ratio in quantity, nonlocal ratio in amount, LTV ratio for local, whether default or not for local, LTV ratio for nonlocal and whether default or not for nonlocal in columns (1)-(6), respectively. In columns (1) and (2), use branch-month panel data and if dependent variable is default situation, use logit regression. Panel A shows the results of the first shock - introducing FinTech credit score in December 2017 and the sample period is from July 2017 to May 2018. Panel B shows the results of the second shock - introducing FinTech Algorithm and the sample period is from January 2018 to November 2018. Standard errors are adjusted for branch-level clustering and reported in parentheses. ***, **, * denote significance levels at 1%, 5%, and 10%, respectively.

	Nonlocal Ratio (Quantity) (1)	Nonlocal Ratio (Amount) (2)	LTV ratio (Local) (3)	Default (Local) (4)	LTV ratio (Nonlocal) (5)	Default (Nonlocal) (6)
Panel A: Changes after the introduction of FinTech credit score						
Changes after introduction	0.047***	0.045***	-0.001	0.058	0.001	0.082
	(0.007)	(0.007)	(0.002)	(0.037)	(0.003)	(0.077)
Observations	1,472	1,472	53,550	53,549	8,568	8,262
Panel B: Changes after the introduction of FinTech Algorithm						
Changes after introduction	0.002	0.015	-0.062***	-0.853***	-0.023***	-1.024***
	(0.011)	(0.011)	(0.004)	(0.059)	(0.008)	(0.131)
Observations	969	969	24,217	24,175	3,849	3,379
Branch FE	YES	YES	YES	YES	YES	YES

Table 4: Overall Difference between Local and Nonlocal Cars

Note: This table reports the results of the following regression

$$Y_{ijt} = \alpha + \beta Nonlocal_{ijt} + \gamma_t + \delta_j + \eta X_{ijt} + \epsilon_{ijt} \tag{1}$$

This table reports the overall difference in LTV ratio and probability of default between local and nonlocal cars. Y_{ijt} is LTV ratio and whether default or not for each loan from July 2016 to December 2018. For default, use logit regression. $Nonlocal_{ijt}$ equals 1 if using nonlocal car as collateral and 0 for local. X_{ijt} are control variables including logarithm of assessed price of the car ($Price(log)$), male ($Male$), age (Age), income ($log(monthly\ income + 1)$), loan repayment type ($FIRST\_INTE$), maturity ($Maturity$), interest rate ($Monthly\ interest\ rate$) and categorical variables for education level, marital status, usage of the loan and loan type. δ_j and γ_t denote branch fixed effects and year-month fixed effects, respectively, and ϵ_{ijt} represents the error term. Standard errors are adjusted for branch-level clustering and reported in parentheses. ***, **, * denote significance levels at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
Panel A: LTV ratio				
Nonlocal	-0.028***	-0.029***	-0.019***	-0.021***
	(0.003)	(0.003)	(0.003)	(0.003)
Observations	161,065	161,065	151,584	151,584
R-squared	0.039	0.064	0.173	0.201
Panel B: Default rate				
Nonlocal	0.186***	0.261***	0.210***	0.250***
	(0.042)	(0.035)	(0.039)	(0.033)
Observations	161,065	161,059	150,909	150,906
Controls			YES	YES
Branch FE		YES		YES
Year-Month FE	YES	YES	YES	YES

Table 5: Effects of FinTech Credit Score Adoption: DID

Note: This table reports the results of the following regression

$$Y_{ijt} = \alpha + \beta_1 Nonlocal_{ijt} + \beta_2 post_t * Nonlocal_{ijt} + \gamma_t + \delta_j + \eta X_{ijt} + \epsilon_{ijt} \tag{2}$$

This table reports the effects of introducing FinTech credit score in December 2017 on LTV ratio (Panel A) and probability of default (Panel B). The sample contains loans only from July 2017 to May 2018. The dependent variable Y_{ijt} is LTV ratio and whether default or not for each loan from July 2017 to May 2018. For default, use logit regression. $Nonlocal_{ijt}$ equals 1 if using nonlocal car as collateral and 0 for local. $post_t$ equals 1 if the loan occurred after the introduction and 0 before. X_{ijt} are control variables including logarithm of assessed price of the car ($Price(log)$), male ($Male$), age (Age), income ($log(monthly\ income + 1)$), loan repayment type ($FIRST\_INTE$), maturity ($Maturity$), interest rate ($Monthly\ interest\ rate$) and categorical variables for education level, marital status, usage of the loan and loan type. δ_j and γ_t denote branch fixed effects and year-month fixed effects, respectively, and ϵ_{ijt} represents the error term. Standard errors are adjusted for branch-level clustering and reported in parentheses. ***, **, * denote significance levels at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
Panel A: LTV ratio				
post × Nonlocal	0.001	0.001	0.000	0.000
	(0.003)	(0.004)	(0.003)	(0.003)
Nonlocal	-0.046***	-0.045***	-0.035***	-0.035***
	(0.004)	(0.004)	(0.003)	(0.004)
Observations	62,118	62,118	62,041	62,041
R-squared	0.018	0.060	0.173	0.209
Panel B: Default rate				
post × Nonlocal	0.012	0.008	-0.011	-0.017
	(0.074)	(0.076)	(0.075)	(0.077)
Nonlocal	0.168***	0.192***	0.191***	0.193***
	(0.058)	(0.054)	(0.056)	(0.052)
Observations	62,118	62,115	62,011	62,008
Controls			YES	YES
Branch FE		YES		YES
Year-Month FE	YES	YES	YES	YES

Table 6: Effects of FinTech Credit Score Adoption: DDD (Comparing to Previous Year)

Note: This table reports the results of the following regression

$$
\begin{aligned}
Y_{ijt} = \alpha + \beta_1 Nonlocal_{ijt} * post_t * TreatedYear_t \quad (3) \\
+ \beta_2 Nonlocal_{ijt} * post_t + \beta_3 Nonlocal_{ijt} * TreatedYear_t + \beta_4 post_t * TreatedYear_t \quad (4) \\
+ \beta_5 Nonlocal_{ijt} + \gamma_t + \delta_j + \eta X_{ijt} + \epsilon_{ijt} \quad (5)
\end{aligned}
$$

This table reports the effects of introducing FinTech credit score in December 2017 on LTV ratio (Panel A) and probability of default (Panel B) using the loans in the previous year as comparison. The sample contains loans from July 2016 to May 2018 (not including June 2017). The dependent variable Y_{ijt} is LTV ratio and whether default or not for each loan from July 2016 to May 2018 (not including June 2017). For default, use logit regression. $Nonlocal_{ijt}$ equals 1 if using nonlocal car as collateral and 0 for local. $TreatedYear$ equals 1 if the month falls into the window period of the actual shocks and equals 0 otherwise. $post_t$ equals 1 if the loan occurred after the introduction and 0 before. X_{ijt} are control variables including logarithm of assessed price of the car ($Price(log)$), male ($Male$), age (Age), income ($log(monthly\ income + 1)$), loan repayment type ($FIRST\_INTE$), maturity ($Maturity$), interest rate ($Monthly\ interest\ rate$) and categorical variables for education level, marital status, usage of the loan and loan type. δ_j and γ_t denote branch fixed effects and year-month fixed effects, respectively, and ϵ_{ijt} represents the error term. Standard errors are adjusted for branch-level clustering and reported in parentheses. ***, **, * denote significance levels at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
Panel A: LTV ratio				
Nonlocal × post × TreatedYear	0.005	0.004	0.005	0.004
	(0.005)	(0.005)	(0.005)	(0.005)
Nonlocal	-0.015***	-0.016***	-0.003	-0.005
	(0.004)	(0.004)	(0.004)	(0.004)
Nonlocal × post	-0.004	-0.003	-0.004	-0.004
	(0.003)	(0.003)	(0.003)	(0.003)
Nonlocal × TreatedYear	-0.031***	-0.029***	-0.032***	-0.030***
	(0.004)	(0.004)	(0.004)	(0.004)
post × TreatedYear	0.042***	0.040***	0.024***	0.019***
	(0.003)	(0.003)	(0.004)	(0.003)
Observations	139,104	139,104	138,239	138,239
R-squared	0.036	0.066	0.148	0.179
Panel B: Default rate				
Nonlocal × post × TreatedYear	-0.016	0.073	-0.029	0.048
	(0.117)	(0.107)	(0.115)	(0.108)
Nonlocal	0.196**	0.339***	0.227***	0.326***
	(0.089)	(0.069)	(0.085)	(0.071)
Nonlocal × post	0.029	-0.062	0.019	-0.059
	(0.107)	(0.090)	(0.106)	(0.093)
Nonlocal × TreatedYear	-0.029	-0.108	-0.032	-0.103
	(0.096)	(0.084)	(0.094)	(0.084)
post × TreatedYear	0.811***	0.786***	0.391***	0.446***
	(0.072)	(0.065)	(0.084)	(0.074)
Observations	139,104	139,101	138,208	138,205
Controls			YES	YES
Branch FE		YES		YES
Year-Month FE	YES	YES	YES	YES

Table 7: Effects of FinTech Algorithm Adoption: DID

Note: This table reports the results of the following regression

$$Y_{ijt} = \alpha + \beta_1 Nonlocal_{ijt} + \beta_2 post_t * Nonlocal_{ijt} + \gamma_t + \delta_j + \eta X_{ijt} + \epsilon_{ijt} \tag{6}$$

This table reports the effects of introducing a FinTech Algorithm in June 2018 on LTV ratio (Panel A) and probability of default (Panel B). The sample contains loans only from January 2018 to November 2018. The dependent variable Y_{ijt} is LTV ratio and whether default or not for each loan from January 2018 to November 2018. For default, we use logit regression. $Nonlocal_{ijt}$ equals 1 if using nonlocal car as collateral and 0 for local. $post_t$ equals 1 if the loan occurred after the introduction and 0 before. X_{ijt} are control variables including logarithm of assessed price of the car ($Price(log)$), male ($Male$), age (Age), income ($log(monthly\ income + 1)$), loan repayment type ($FIRST\_INTE$), maturity ($Maturity$), interest rate ($Monthly\ interest\ rate$) and categorical variables for education level, marital status, usage of the loan and loan type. δ_j and γ_t denote branch fixed effects and year-month fixed effects, respectively, and ϵ_{ijt} represents the error term. Standard errors are adjusted for branch-level clustering and reported in parentheses. ***, **, * denote significance levels at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
Panel A: LTV ratio				
post × Nonlocal	0.042***	0.040***	0.026***	0.023***
	(0.006)	(0.006)	(0.005)	(0.005)
Nonlocal	-0.042***	-0.042***	-0.032***	-0.032***
	(0.004)	(0.005)	(0.004)	(0.004)
Observations	28,066	28,066	21,484	21,484
R-squared	0.066	0.092	0.335	0.359
Panel B: Default rate				
post × Nonlocal	-0.158	-0.134	-0.055	-0.044
	(0.139)	(0.140)	(0.170)	(0.175)
Nonlocal	0.209***	0.208***	0.199***	0.177***
	(0.073)	(0.066)	(0.074)	(0.067)
Observations	28,066	28,020	21,462	21,419
Controls			YES	YES
Branch FE		YES		YES
Year-Month FE	YES	YES	YES	YES

Table 8: Effects of FinTech Algorithm Adoption: DDD (Comparing to Previous Year)

Note: This table reports the results of the following regression

$$Y_{ijt} = \alpha + \beta_1 Nonlocal_{ijt} * post_t * TreatedYear_t \tag{7}$$
$$+ \beta_2 Nonlocal_{ijt} * post_t + \beta_3 Nonlocal_{ijt} * TreatedYear_t + \beta_4 post_t * TreatedYear_t \tag{8}$$
$$+ \beta_5 Nonlocal_{ijt} + \gamma_t + \delta_j + \eta X_{ijt} + \epsilon_{ijt} \tag{9}$$

This table reports the effects of introducing a FinTech Algorithm in June 2018 on LTV ratio (Panel A) and probability of default (Panel B) using the loans in the previous year as comparison. The sample contains loans from January 2017 to November 2018 (not including December 2017). The dependent variable Y_{ijt} is LTV ratio and whether default or not for each loan from January 2017 to November 2018 (not including December 2017). For default, use logit regression. $Nonlocal_{ijt}$ equals 1 if using nonlocal car as collateral and 0 for local. $TreatedYear$ equals 1 if the month falls into the window period of the actual shocks and equals 0 otherwise. $post_t$ equals 1 if the loan occurred after the introduction and 0 before. X_{ijt} are control variables including logarithm of assessed price of the car ($Price(log)$), male ($Male$), age (Age), income ($log(monthly\ income + 1)$), loan repayment type ($FIRST\_INTE$), maturity ($Maturity$), interest rate ($Monthly\ interest\ rate$) and categorical variables for education level, marital status, usage of the loan and loan type. δ_j and γ_t denote branch fixed effects and year-month fixed effects, respectively, and ϵ_{ijt} represents the error term. Standard errors are adjusted for branch-level clustering and reported in parentheses. ***, **, * denote significance levels at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
Panel A: LTV ratio				
Nonlocal × post × TreatedYear	0.067***	0.064***	0.052***	0.048***
	(0.007)	(0.008)	(0.006)	(0.007)
Nonlocal	-0.019***	-0.020***	-0.007**	-0.008**
	(0.004)	(0.005)	(0.003)	(0.004)
Nonlocal × post	-0.026***	-0.024***	-0.026***	-0.025***
	(0.004)	(0.004)	(0.003)	(0.003)
Nonlocal × TreatedYear	-0.024***	-0.022***	-0.025***	-0.026***
	(0.004)	(0.004)	(0.003)	(0.003)
post × TreatedYear	-0.056***	-0.056***	-0.105***	-0.110***
	(0.007)	(0.007)	(0.012)	(0.011)
Observations	103,560	103,560	96,978	96,978
R-squared	0.041	0.067	0.193	0.223
Panel B: Default rate				
Nonlocal × post × TreatedYear	-0.086	-0.102	0.005	-0.009
	(0.162)	(0.167)	(0.190)	(0.196)
Nonlocal	0.250***	0.288***	0.269***	0.269***
	(0.088)	(0.082)	(0.082)	(0.079)
Nonlocal × post	-0.072	-0.056	-0.061	-0.045
	(0.094)	(0.094)	(0.091)	(0.091)
Nonlocal × TreatedYear	-0.041	-0.046	-0.065	-0.067
	(0.108)	(0.110)	(0.108)	(0.110)
post × TreatedYear	-1.447***	-1.526***	-3.244***	-3.215***
	(0.202)	(0.199)	(0.507)	(0.510)
Observations	103,560	103,533	96,946	96,922
Controls			YES	YES
Branch FE		YES		YES
Year-Month FE	YES	YES	YES	YES

Table 9: Robustness Tests by Adding the LTV Ratio as Control

Note: This table reports the results of the following regression

$$Y_{ijt} = \alpha + \beta_1 Nonlocal_{ijt} + \beta_2 post_t * Nonlocal_{ijt} + \gamma_t + \delta_j + \eta X_{ijt} + \epsilon_{ijt} \tag{10}$$

$$\begin{aligned} Y_{ijt} = \alpha &+ \beta_1 Nonlocal_{ijt} * post_t * TreatedYear_t && (11)\\ &+ \beta_2 Nonlocal_{ijt} * post_t + \beta_3 Nonlocal_{ijt} * TreatedYear_t + \beta_4 post_t * TreatedYear_t && (12)\\ &+ \beta_5 Nonlocal_{ijt}\gamma_t + \delta_j + \eta X_{ijt} + \epsilon_{ijt} && (13)\end{aligned}$$

This table reports the robustness test results by adding the LTV ratio as a control variable in logit regressions on default. We examining the effects of introducing FinTech credit score in Panels A and B and FinTech Algorithm in Panels C and D. The dependent variable Y_{ijt} is whether borrowers default on a loan. $Nonlocal_{ijt}$ equals 1 if using nonlocal car as collateral and 0 for local. $TreatedYear$ equals 1 if the month falls into the window period of the actual shocks and equals 0 otherwise. $post_t$ equals 1 if the loan occurred after the introduction and 0 before. X_{ijt} are control variables including LTV ratio ($Loan\ proportion$), logarithm of assessed price of the car ($Price(log)$), male ($Male$), age (Age), income ($log(monthly\ income + 1)$), loan repayment type ($FIRST\_INTE$), maturity ($Maturity$), interest rate ($Monthly\ interest\ rate$) and categorical variables for education level, marital status, usage of the loan and loan type. δ_j and γ_t denote branch fixed effects and year-month fixed effects, respectively, and ϵ_{ijt} represents the error term. Standard errors are adjusted for branch-level clustering and reported in parentheses. ***, **, * denote significance levels at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
Panel A: Introduction of FinTech Credit Score: DID				
post × Nonlocal	0.012	0.008	-0.007	-0.013
	(0.074)	(0.076)	(0.076)	(0.077)
Nonlocal	0.168***	0.192***	0.287***	0.290***
	(0.058)	(0.054)	(0.057)	(0.053)
Observations	62,118	62,115	62,011	62,008
Panel B: Introduction of FinTech Credit Score: DDD				
Nonlocal × post × TreatedYear	-0.016	0.073	-0.042	0.036
	(0.117)	(0.107)	(0.116)	(0.109)
Nonlocal	0.196**	0.339***	0.234***	0.335***
	(0.089)	(0.069)	(0.085)	(0.071)
Two-way interactions	Yes	Yes	Yes	Yes
Observations	139,104	139,101	138,208	138,205
Panel C: Introduction of FinTech Algorithm: DID				
post × Nonlocal	-0.158	-0.134	-0.081	-0.065
	(0.139)	(0.140)	(0.171)	(0.176)
Nonlocal	0.209***	0.208***	0.265***	0.242***
	(0.073)	(0.066)	(0.073)	(0.068)
Observations	28,066	28,020	21,462	21,419
Panel D: Introduction of FinTech Algorithm: DDD				
Nonlocal × post × TreatedYear	-0.086	-0.102	-0.112	-0.123
	(0.162)	(0.167)	(0.190)	(0.197)
Nonlocal	0.250***	0.288***	0.292***	0.290***
	(0.088)	(0.082)	(0.080)	(0.079)
Two-way interactions	Yes	Yes	Yes	Yes
Observations	103,560	103,533	96,946	96,922
All Panels				
Controls			YES	YES
Branch FE		YES		YES
Year-Month FE	YES	YES	YES	YES

Table 10: Robustness Tests using Alternative Default Measures

Note: This table reports the results of the following regression

$$Y_{ijt} = \alpha + \beta_1 Nonlocal_{ijt} + \beta_2 post_t * Nonlocal_{ijt} + \gamma_t + \delta_j + \eta X_{ijt} + \epsilon_{ijt} \quad (14)$$

$$Y_{ijt} = \alpha + \beta_1 Nonlocal_{ijt} * post_t * TreatedYear_t \quad (15)$$
$$+ \beta_2 Nonlocal_{ijt} * post_t + \beta_3 Nonlocal_{ijt} * TreatedYear_t + \beta_4 post_t * TreatedYear_t \quad (16)$$
$$+ \beta_5 Nonlocal_{ijt} \gamma_t + \delta_j + \eta X_{ijt} + \epsilon_{ijt} \quad (17)$$

This table reports the robustness test results using alternative definitions of a default. We examining the effects of introducing FinTech credit score in Panels A and B and FinTech Algorithm in Panels C and D. The dependent variable Y_{ijt} is whether maximum default days more than zero or not for each loan. The time period and variable definition are the same as the corresponding regressions before. $Nonlocal_{ijt}$ equals 1 if using nonlocal car as collateral and 0 for local. $TreatedYear$ equals 1 if the month falls into the window period of the actual shocks and equals 0 otherwise. $post_t$ equals 1 if the loan occurred after the introduction and 0 before. X_{ijt} are control variables including logarithm of assessed price of the car ($Price(log)$), male ($Male$), age (Age), income ($log(monthly\ income + 1)$), loan repayment type ($FIRST\_INTE$), maturity ($Maturity$), interest rate ($Monthly\ interest\ rate$) and categorical variables for education level, marital status, usage of the loan and loan type. δ_j and γ_t denote branch fixed effects and year-month fixed effects, respectively, and ϵ_{ijt} represents the error term. Standard errors are adjusted for branch-level clustering and reported in parentheses. ***, **, * denote significance levels at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
Panel A: Introduction of FinTech Credit Score: DID				
post × Nonlocal	-0.037	-0.053	-0.067	-0.076
	(0.053)	(0.057)	(0.054)	(0.056)
Nonlocal	0.296***	0.156***	0.328***	0.162***
	(0.058)	(0.054)	(0.057)	(0.053)
Observations	62,118	62,118	62,034	62,034
Panel B: Introduction of FinTech Credit Score: DDD				
Nonlocal × post × TreatedYear	-0.126	-0.094	-0.166**	-0.133*
	(0.078)	(0.079)	(0.078)	(0.079)
Nonlocal	0.171**	0.103*	0.201***	0.100
	(0.069)	(0.061)	(0.070)	(0.065)
Two-way interactions	Yes	Yes	Yes	Yes
Observations	139,104	139,104	138,232	138,232
Panel C: Introduction of FinTech Algorithm: DID				
post × Nonlocal	-0.157*	-0.144*	-0.084	-0.080
	(0.081)	(0.084)	(0.105)	(0.106)
Nonlocal	0.248***	0.086*	0.237***	0.059
	(0.063)	(0.050)	(0.062)	(0.052)
Observations	28,066	28,061	21,478	21,474
Panel D: Introduction of FinTech Algorithm: DDD				
Nonlocal × post × TreatedYear	-0.131	-0.126	-0.050	-0.063
	(0.091)	(0.102)	(0.115)	(0.128)
Nonlocal	0.315***	0.202***	0.352***	0.198***
	(0.060)	(0.061)	(0.063)	(0.061)
Two-way interactions	Yes	Yes	Yes	Yes
Observations	103,560	103,559	96,972	96,972
All Panels				
Controls			YES	YES
Branch FE		YES		YES
Year-Month FE	YES	YES	YES	YES

Table 11: Robustness Tests using the Sample of Active Stores

Note: This table reports the results of the following regression

$$Y_{ijt} = \alpha + \beta_1 Nonlocal_{ijt} + \beta_2 post_t * Nonlocal_{ijt} + \gamma_t + \delta_j + \eta X_{ijt} + \epsilon_{ijt} \tag{18}$$

$$\begin{aligned} Y_{ijt} = \alpha &+ \beta_1 Nonlocal_{ijt} * post_t * TreatedYear_t & (19) \\ &+ \beta_2 Nonlocal_{ijt} * post_t + \beta_3 Nonlocal_{ijt} * TreatedYear_t + \beta_4 post_t * TreatedYear_t & (20) \\ &+ \beta_5 Nonlocal_{ijt} + \gamma_t + \delta_j + \eta X_{ijt} + \epsilon_{ijt} & (21) \end{aligned}$$

This table reports the robustness test results by restricting our sample to active branches that have been extending loans for no less than 12 months between 2017 and 2018. We examining the effects of introducing FinTech credit score in Panels A and B and FinTech Algorithm in Panels C and D. The sample contains 173 active branches. For DID, it contains loans from January 2018 to November 2018 and for DDD contains loans from January 2017 to November 2018 (not including December 2017). The dependent variable Y_{ijt} is LTV ratio. $Nonlocal_{ijt}$ equals 1 if using nonlocal car as collateral and 0 for local. $TreatedYear$ equals 1 if the month falls into the window period of the actual shocks and equals 0 otherwise. $post_t$ equals 1 if the loan occurred after the introduction and 0 before. X_{ijt} are control variables including logarithm of assessed price of the car ($Price(log)$), male ($Male$), age (Age), income ($log(monthly\ income + 1)$), loan repayment type ($FIRST\_INTE$), maturity ($Maturity$), interest rate ($Monthly\ interest\ rate$) and categorical variables for education level, marital status, usage of the loan and loan type. δ_j and γ_t denote branch fixed effects and year-month fixed effects, respectively, and ϵ_{ijt} represents the error term. Standard errors are adjusted for branch-level clustering and reported in parentheses. ***, **, * denote significance levels at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
Panel A: Effect of FinTech Algorithm on LTV ratio: DID				
post × Nonlocal	0.041***	0.040***	0.026***	0.023***
	(0.006)	(0.006)	(0.005)	(0.005)
Nonlocal	-0.042***	-0.042***	-0.031***	-0.032***
	(0.005)	(0.005)	(0.004)	(0.004)
Observations	26,601	26,601	20,350	20,350
R-squared	0.067	0.092	0.340	0.363
Panel B: Effect of FinTech Algorithm on LTV ratio: DDD				
Nonlocal × post × TreatedYear	0.067***	0.065***	0.052***	0.049***
	(0.007)	(0.008)	(0.006)	(0.007)
Nonlocal	-0.018***	-0.019***	-0.007**	-0.008**
	(0.004)	(0.005)	(0.003)	(0.004)
Two-way interactions	Yes	Yes	Yes	Yes
Observations	100,378	100,378	94,127	94,127
R-squared	0.041	0.065	0.193	0.221
All Panels				
Controls			YES	YES
Branch FE		YES		YES
Year-Month FE	YES	YES	YES	YES