Fintech and Gender Discrimination

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Current Version: January 2023

Abstract

Using data from a lending platform that switched from a human-based to a machine learning-based system, we find that fintech may increase gender discrimination. The rationale is that machine learning algorithms allow the platform to better decipher differences in borrower preferences between female and male borrowers. Specifically, after the switch, the platform assigned higher interest rates and better credit ratings to less price-sensitive female borrowers. These results are not driven by changes in borrower credit risk or lender preferences. Instead, the behavior is consistent with the platform's attempt to maximize its revenue by applying price discrimination to female borrowers.

Keywords: Fintech, Gender discrimination, Peer-to-peer lending, Machine learning, Credit rating
JEL code: G41, G51, J16

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1 Introduction

A gender gap exists in the credit lending market. According to the World Bank Global Findex Database (Demirguc-Kunt et al., 2017), women consistently comprise a lower proportion of borrowers at formal financial institutions relative to men across different countries and over time.[1] An underlying reason for this gap is that bank officers charge high interest rates and grant low loan amounts to female borrowers (e.g., Muravyev, Talavera, and Schäfer, 2009; Beck, Behr, and Madestam, 2018; De Andrés, Gimeno, and de Cabo, 2021).[2] In recent years, the rise of financial technology (fintech) has featured the application of algorithms in financial services. Given that loan approval decisions mostly rely on bank officers' judgment, we wonder whether the adoption of algorithms in lieu of bank officers in the loan process would mitigate such gender bias.

One of the most notable advantages of fintech systems is that they do not rely on subjective human judgment. This means that fintech systems would treat borrowers equally regardless of gender, ethnicity, nationality, and other attributes (Philippon, 2019). In contrast, in traditional banking business, bank officers inevitably consider their owning value, experience, and cultural background when assessing lenders, particularly when the assessment is made via face-to-face communication (e.g., Blanchflower, Levine, and Zimmerman, 2003; Black, Boehm, and DeGennaro, 2003; Fisman, Paravisini, and Vig, 2017). Thus, if female borrowers are not fairly treated by bank officers in traditional banking, then we expect the adoption of algorithms in fintech lending to reduce gender discrimination.

In addition to fintech lenders' ability to better analyze and price credit risk (Fuster et al., 2019; Berg et al., 2020), the use of algorithms in the lending process could also uncover borrower characteristics unrelated to creditworthiness, such as borrowers' preferences or personalities (Tantri, 2021; Bartlett et al., 2022; Fuster et al., 2022;). Fintech lenders can utilize such information and offer loans with differential prices that are not based on borrowers' credit risk. For example, less price-sensitive borrowers could be charged higher interest rates even if they are not riskier. If the fintech system identifies a weakness in female borrowers relative to male borrowers, then

[1] 29.59% male borrowed from a formal financial institute and 27.15% female borrowed from a formal financial institute around the world. In term of developing countries, 23.44% male borrowed from a formal financial institute and 20.44% female borrowed from a formal financial institute. More information could be found in https://www.worldbank.org/en/publication/globalfindex.

[2] We define the gender bias in the lending market as the case that female borrowers are charged at higher interest rates or less likely to obtain funding compared to those male borrowers who have the same level of credit risk. In our study, gender discrimination does not refer to statistical discrimination and mainly refers to taste-based discrimination or other types.

unfavorable loan options may be given to female borrowers, which would worsen gender discrimination in the credit lending market.

To test the impact of fintech on gender discrimination, we use data from a Chinese peer-to-peer (P2P) lending platform. As the largest P2P platform in China, the platform has enabled 17.9 million borrowers to obtain $11.8 billion in unsecured credit by 2019. The business model of this lending platform is similar to that of platforms in the US such as LendingClub and Proper.com. A borrower submits her application to the platform and simultaneously provides various personal information to the platform. Using this information, the platform assigns an interest rate and credit rating to the application.

After seeing the assigned interest rate and credit rating, the borrower can decide whether she wants to move forward with or withdraw the application. If the borrower accepts the assigned interest rate and credit rating, then the application will be posted on the platform. After observing the loan's interest rate and credit rating, lenders will decide whether and how much to contribute to the loan. If the application is fully funded within a week, then the loan is originated. The platform charges origination and servicing fees from the originated loan.

The assigned interest rate and credit rating are crucial to the success of the entire deal on the platform. Therefore, the platform devotes considerable resources to constructing a reliable rating system. Initially, the platform employed professional staff to manually assess loan applications, i.e., an employee would have to use his/her judgement to assign an interest rate and a credit rating to each loan application. On March 24th, 2015, the platform adopted a machine learning-based system. The new system uses a dynamic and adaptive machine learning algorithm to assess the default risk of each loan application based on all the available information on the applicant. The system automatically generates the interest rate and credit rating for each loan application.

Using these data to identify the effect of fintech on gender discrimination offers three advantages. First, the lending platform switched from a manual system to a machine learning-based system during our sample period, which allows us to identify the change in lending caused by the transition. In contrast, most existing papers rely on cross-sectional comparisons between fintech and non-fintech credit providers (e.g., Fuster et al., 2019; Chen, Huang, and Ye, 2020; Bartlett et al., 2022).

Second, the machine learning algorithm captures the preferences of borrowers by analyzing their behaviors on the platform. In this study, we can observe the withdrawal decisions that loan applicants make after observing the interest rates and credit ratings assigned by the platform, which allows us to assess applicants' price sensitivity. The machine learning algorithm can also detect the withdrawal behavior of borrowers and incorporate this information into pricing strategy.

Third, a necessary condition for gender discrimination in the credit market is that there are some market frictions, such as imperfect credit market competition or search frictions. In countries with more developed financial and credit markets, these frictions are likely to be small. We are therefore more likely to find evidence of such discrimination in countries such as China, in which the credit market is relatively less developed.

As a preliminary analysis, we perform a univariate difference-in-differences (DID) test. We find that after the adoption of the machine learning-based system, the average interest rate for female borrowers increased by 0.449% relative to that for male borrowers. In the multivariate DID analysis, we find that the interest rates assigned by the lending platform to female borrowers, relative to male borrowers, increased by approximately 0.446% after the transition. The results remain robust after controlling for borrower and loan characteristics. In particular, the results remain robust after controlling for credit rating fixed effects.

To mitigate the concern that the results may be driven by unobservable trend differences between male and female borrowers, we conduct an event study to examine the changes in interest rates around the adoption of the machine learning-based system. We find that the divergence in interest rates between female and male applicants occurs only after—and not before—the transition from the manual system to the machine learning-based system, suggesting that the results are likely to be driven by the transition itself.

These results may, however, still be driven by heterogeneous characteristics between male and female borrowers before and after the transition from the manual system to the machine learning-based system. To this end, we show two additional sets of robustness tests. First, focusing on a subsample of repeated borrowers, we still find the same results with borrower fixed effects, suggesting that the results are unlikely to be driven by time-invariant borrower characteristics. Second, we conduct our regressions in a matched sample in which we pair male borrowers to identical female borrowers based on all observable variables. The results are still consistent with our baseline results.

In addition, we conduct two placebo tests to ensure that our results are not driven by chance. First, we randomly assign some borrowers in our sample as pseudo borrowers and then repeat our baseline regressions for 1,000 rounds. Second, we randomly redistribute our observations to different dates with our sample, which allows us to update the time-related variables used in our regressions based on the newly assigned application date and then re-estimate our model for 1,000 rounds. Both placebo tests indicate that a random sample can only generate a very close to zero coefficient in the DID specification. As a result, our results are less likely to be driven by chance.

Our findings are also robust among different subgroups of borrowers. First, female borrowers are more likely to receive higher interest rates after using the machine learning-based system regardless of whether the borrower is from a developed region (Eastern China) or a less-developed region (Central and Western China). Second, gender discrimination in interest rates assigned by the machine learning-based system exists for both younger and older borrowers.

We then try to identify why the machine learning-based system superficially increases the interest rate for female borrowers and argue that our findings are consistent with price discrimination and the platform's incentive to maximize revenue. The platform generates revenue from origination and servicing fees and hence has a stronger incentive to maximize the number of loans originated. If the platform assigns a higher interest rate on a loan application, then the applicant could withdraw the application, especially if the applicant is price-sensitive. On the other hand, an application with a higher interest rate is more likely to be funded by potential lenders, especially if the credit rating is not low. As such, assigning higher interest rates to less price-sensitive borrowers would maximize the platform's revenue.

To confirm that the increases in interest rates for female borrowers are driven by price discrimination against less price-sensitive borrowers, it is necessary to verify that female borrowers are less price-sensitive on average.[3] To do so, we examine borrowers' withdrawal decisions after they observe the interest rates assigned by the platform. Price-sensitive borrowers are more likely to withdraw their applications after seeing higher interest rates assigned to their applications, and vice versa. Regressing the withdrawal decision on the interaction term between the assigned interest rates and gender, we indeed find that female borrowers are less likely to withdraw their applications when higher interest rates are assigned, providing direct evidence that they are less price sensitive.

[3] It is not necessary although that the platform uses gender to infer the price-sensitivity. The machine learning algorithm can use all the information the platform has to assess the price sensitivity, and it suffices that female borrowers are less price-sensitive than male borrower on average.

We then examine whether the strategy helps the platform achieve its goal of increasing approval rates for female borrowers. To this end, we find that, without controlling for the assigned interest rates, the approval rates for female applicants increase relative to male applications after the transition. However, after controlling for the interest rates, the effect becomes much smaller. These results suggest that the platform is able to successfully increase the approval rates of female borrowers with the price discrimination strategy.

Finally, we perform four tests to verify that the results are not driven by other alternative explanations. First, we find that the credit ratings of female borrowers improve after the transition, suggesting that the changes in credit risk are unlikely to explain the increases in interest rates for female borrowers. Second, we show that the default behaviors of female borrowers do not change significantly after the transition to the machine learning-based system, suggesting that the increases in interest rates for female borrowers cannot be explained by an increase in default risk. Third, we find that the prepayment behaviors between female and male borrowers are not significantly different and are consistent over time, suggesting that the different interest rates are not compensation for the possible loss of interest revenue of lenders. Fourth, we check the supply side on the platform and find that the attitudes of lenders do not change before and after the transition to the machine learning-based system between male and female borrowers, suggesting that the effects are not driven by the supply side of the platform.

Overall, our empirical findings illustrate that the adoption of a machine learning-based system increases the cost of debt for female borrowers (intensive margin) and allows more female borrowers to access credit (extensive margin). Based on our estimates, female borrowers would incur an additional 9% in costs to obtain additional credit. This striking cost, which is was induced by the adoption of machine learning algorithms, raises substantial concerns about gender equity in the credit market.

Our paper contributes to the literature on discrimination and gender inequality in the credit market. First, most papers focusing on the US find evidence of racial discrimination in many different types of credit markets (Munnell et al. 1996; Blanchflower, Levine, and Zimmerman 2003; Chatterji and Seamans 2012; Butler, Mayer, and Weston 2020; Chu, Huang, and Zhang 2021; Chu, Ma, and Zhang 2021). Papers focusing on less developed countries often find evidence of gender inequality in access to credit (Asiedu et al. 2013; Ongena and Popov 2016; Beck, Behr, and Madestam 2018). These studies focus on either taste-based discrimination or risk-based statistical discrimination. Our paper contributes to this strand of literature by studying the possibility of using non-risk information to engage in price discrimination.

Second, our paper also contributes to the growing literature on fintech, particularly the impact of fintech lending[4]. The literature has mostly focused on efficiency and equity issues in fintech.[5] Regarding efficiency, studies find that fintech improves lending efficiency. For example, Fuster et al. (2019) find that fintech lenders process mortgage applications faster and that speed increases do not lead to higher default rates. Berg et al. (2020) find that using digital footprints collected by fintech platforms can help reduce default rates. Tantri (2021) also finds that machine learning algorithms improve the efficiency of fintech platforms.

Regarding equity, however, the evidence is more mixed. Bartlett et al. (2022) find that fintech lenders discriminate less but still engage in substantial statistical discrimination. Fuster et al. (2022) also find that machine learning algorithms used by fintech platforms can disproportionally hurt black and Hispanic borrowers. On the other hand, Tantri (2021) finds that machine learning algorithms do not compromise equity in lending.

Our paper contributes to the literature on equity along two dimensions. First, most papers focus on whether fintech lenders are more capable of engaging in statistical discrimination, i.e., using non-risk borrower characteristics to infer credit risk. Our paper, however, focuses on whether machine learning algorithms can use observable characteristics to infer non-risk preference information for price discrimination. In particular, we show that the algorithms are able to identify price-insensitive borrowers and then charge them higher interest rates. Second, while most papers focus on race-related concerns, our paper focuses on gender-related equity concerns.

The rest of the paper is organized as follows. Section 2 discusses the institutional background. Section 3 describes the sample construction and variable definitions. Section 4 presents the main empirical results. Section 5 discusses the channels through which the machine learning algorithms discriminate. Section 6 concludes.

[4] For example, a review by Berg, Fuster, and Puri (2022).

[5] Other papers focus on the substitutatiblity or complimentairy between FinTech lending and traditional banking (Tang 2019; De Roure, Pelizzon, and Thakor 2022; Balyuk 2020; Balyuk, Berger, and Hackney 2020; Di Maggio and Yao 2021) and the regulatory issues associated with FinTech (Buchak et al. 2018).

2 Institutional background, data, and descriptive statistics

2.1 Institutional background

The world's first peer-to-peer (P2P) lending platform, Zopa, was established in the UK in 2005. The first US P2P lending platform, Prosper Marketplace, was established in February 2006, and was soon followed by LendingClub, which would become the largest US P2P lending platform. Over the past 15 years, P2P lending platforms have grown dramatically around the world. For example, according to a report published by Precedence Research, the global P2P market size was valued at $83.8 billion in 2021 and is expected to reach $705.8 billion by 2030.[6]

On P2P lending platforms, individual borrowers can disclose their information and request credit from potential lenders. Then, potential lenders would invest directly in consumer loans without any financial intermediations. Usually, interest rates and lending terms are set by the platforms. Compared to banks, P2P lending platforms offer online services with looser eligibility requirements for borrowers and higher investment returns for lenders. The default rates for P2P loans are also higher than those for banks.

The business model of P2P lending achieved great success in China in the 2010s since the first Chinese P2P lending platform, PaiPaiDai, was introduced in 2007. In 2010, the transaction volume of the Chinese P2P lending market was only $35 million. Since then, it has grown to become the world's largest P2P lending market, peaking in 2017 with approximately five active million lenders who provided over 200 billion RMB (approximately $28 billion) loans every month across more than 3,000 Chinese P2P platforms (Gu, Gui, and Huang, 2022).

After the rapid expansion of the P2P lending market in China, many platforms went bankrupt due to the lack of risk management. Millions of investors suffered heavy losses, which caused serious concerns about social unrest. The Chinese government began to impose strict regulations on these platforms in 2016. By December 2019, there were still approximately 300 P2P lending platforms in China. By mid-November 2020, all P2P platforms in China were completely shut down

We obtain our data from one of the major P2P platforms in China. The platform originated $755.2 million (equivalent to 5.1 billion RMB) in loans in 2015 and became the largest P2P platform in China. According to its financial reports, this platform has facilitated 17.9 million borrowers to access $11.8 billion (82.2 billion RMB) of unsecured credit before ending its business

[6] See, https://www.precedenceresearch.com/peer-to-peer-lending-market.

in 2019.[7] Unlike many other platforms, this platform does not provide any guarantees on borrowing. Although the loans originated on the platform are not securitized, they still attracted over 712,000 investors by the end of 2019. Each investor also makes a significant investment. The average investment amount per investor per year is approximately $14,200 (approximately 100,000 RMB).

To submit a loan application, a borrower must first create an account and provide her personal information to the platform. Then, the borrower submits the intended amount and maturity of the loan to the platform.[8] The platform assigns both an interest rate and a credit rating to the loan application based on the information provided by the borrower.

To have her loan application listed on the platform, the borrower needs to accept the assigned interest rate and credit rating. After this step, potential lenders can access the information that the borrower provided to the platform and invest in the loan application at any amount starting from approximately $7 (50 RMB). If the total amount invested into the loan application reaches the required amount within one week after it is listed, then the loan is originated. The platform charges processing and servicing fees from the borrower. Otherwise, the loan application is unsuccessful. Figure 1 illustrates the entire process of the loan application.

[Insert Figure 1 Here]

2.2 Switching from a manual system to a machine learning-based system

Before March 24, 2015, credit ratings and interest rates were assessed manually by the professional staff of the platform. These staff read the information provided by the borrowers and the loan applications and assessed credit risk based on a rubric. In general, the rubric assigns certain marks for each item of the information that borrowers provide to the platform. The rating staff evaluate all items one by one and then sum up all marks. Based on the final score, the staff assign an interest rate and a credit rating to a loan application within a range suggested by the guideline.

The manual rating system has several flaws. First, it is time-consuming. This system relies on the staff to review all the borrowers' materials. As a result, the system cannot respond to the loan application immediately and borrowers must wait to receive feedback from the platform on their

[7] The platform still exists, but the business model changed. After 2019, the platform does not allow individual investors to bid on loan applications.

[8] The maximum amount and term of the loan are restricted by the platform.

loan applications. Second, the manual rating system is costly and restricts the growth of the platform. With the expansion of the business, the platform receives an increasing number of applications every day. To respond to these applications efficiently, the platform must employ more staff. Third, the rating process tends to be subjective, i.e., the final interest rates and credit ratings are highly dependent on the personal judgment of the staff member.

The platform started to use a machine learning-based system to assess the credit ratings and interest rates of loan applications on March 24, 2015. According to publicly disclosed information on the platform, this system uses dynamic and adaptive machine learning algorithms to assess the default risk of each loan application based on all available information. The machine learning-based system leverages a big database built up gradually through the platform's operations. Such a vast amount of data lays a strong foundation for the use of machine learning algorithms to optimize the credit scoring model on a continuing basis. It can update automatically with the latest data.

Different algorithms are applied to each type of prospective borrower in assessing the potential risks associated with their features and the credit scoring model generates a credit rating for each of the prospective borrowers based on the results of the initial assessment. A new credit rating is generated each time a borrower applies for a loan, which also changes the borrower's interest rate. The platform applies various machine learning techniques to the data collected. Through monitoring model performance as well as variable consistency, the system can evaluate the effectiveness of existing variables while discovering new ones. The credit scoring model is then optimized by adjusting the group of variables used.

The platform also claims that this machine learning-based system was granted the Financial Innovative Award of 2015 by the local government for the innovative use of technology in the field of risk management, crowning the platform as the only such titleholder in the online consumer finance marketplace industry.

2.3 Data

We use a randomized sample of loans drawn from over five million loan applications from the platform over the period from January 2014 to November 2015, which includes the transition date of March 24, 2015. We start our sample in January 2014 because the business model of this P2P platform was not yet well established and stable prior to 2014.[9] We end our sample in December 2015 because the Chinese government implemented stricter regulations during this month following mass defaults across many P2P platforms. For example, before 2012, only 16 P2P lending platforms in China collapsed; however, in 2016, 1,717 platforms shut down.

Our primary sample includes only loan applications from first-time borrowers. First-time borrowers do not have any records of their credit performance on the platform. Both the platform and potential lenders can only rely on the information provided by these borrowers to evaluate their credit risk. In further analysis, we also use a sample of repeated borrowers who try to borrow from the platform multiple times. In our sample, 56.17% of loan applications are placed by repeat borrowers.[10] Overall, our sample consists of 548,039 loan applications from first-time borrowers, 12.6% of which are from female borrowers.

Figure 2 Panel A presents the geographical distribution of the loan application density, which is the number of applications per thousand people across the provinces in China. The borrowers of the platform are widely distributed across all provinces in mainland China. More populous provinces have more borrowers. The figure tends to indicate that our sample is geographically unbiased. Panel B presents the geographical distribution of the density of loan applications from female borrowers. In most provinces, female applicants comprise more than 10% of applications. Interestingly, the proportion of female borrowers is large both in large cities, such as Beijing and Shanghai, and in less-developed provinces, such as Xinjiang and Yunnan.

[Insert Figure 2 Here]

We also plot the number of loan applications in our sample by month in Figure 3 Panel A. Business on the platform expanded rapidly from 2014 to 2015. The number of applications grew continuously except in February due to the Spring Festival holiday in China. Notably, the size of loan applications increases even faster after the adoption of machine learning algorithms. The timely response of the machine learning-based system drove the expansion of the platform's business. Figure 3 Panel B describes the proportion of female applications by month, which is consistently stable over time and does not change before or after the adoption of the machine learning-based system.

[9] Before 2014, this platform also operates for small business loans, auto installment loans and other types of loans.
[10] According to the financial reports of the platform, 55.7% of the loans are issued to the borrowers who had successfully borrowed on the platform before in 2015.

[Insert Figure 3 Here]

2.4 Variable construction

2.4.1 Loan pricing and outcome variables

The loan pricing variable is the annual interest rate (*Interest Rate*) on a loan application assigned by the platform. We use the loan application's credit rating as the key determinant of loan pricing. The platform categorizes credit ratings into six levels from the highest rating "A" to the lowest rating "F."[11] *Credit Rating* is coded as one to six, with one indicating the lowest credit rating "F" and six indicating the highest credit rating A.

In further analyses, we construct the three sets of loan outcome variables. First, we study whether the borrower withdraws the loan application and whether the loan application is successfully funded. *Withdrawn* is a dummy variable that is equal to one if the borrower withdraws the loan application within one week after the loan application is posted online and zero otherwise. *Funded* is a dummy variable that is equal to one if the borrower successfully receives the loan in the platform and zero otherwise.

Second, we examine the delinquency of the loan. $Delinquency_{30}$ is a dummy variable that is equal to one if the loan is overdue more than 30 days and zero otherwise. $Delinquency_{45}$ is a dummy variable that is equal to one if the loan is overdue more than 45 days and zero otherwise. $Delinquency_{90}$ is a dummy variable that is equal to one if the loan is overdue more than 90 days and zero otherwise.

Third, we test the prepayment of the loan. $Prepayment_{30}$ is a dummy variable that is equal to one if the loan is prepaid at least 30 days before the maturity date and zero otherwise. $Prepayment_{45}$ is a dummy variable that is equal to one if the loan is prepaid at least 45 days before the maturity date and zero otherwise. $Prepayment_{90}$ is a dummy variable that is equal to one if the loan is prepaid at least 90 days before the maturity date and zero otherwise.

2.4.2 Female borrowers and control variables

Our variable of interest is the dummy variable *Female*, which is equal to one if the borrower is female and zero otherwise. This information is provided by the borrowers when they create an

[11] Borrowers who have guarantees on their loan applications would receive an exceptional AA credit rating. In the study, we exclude all loan applications with guarantees in our sample.

account. It is also cross-checked with other available information, such as identity codes and credit reports, to ensure accuracy. In addition, the borrower does not have an incentive to misrepresent gender because the platform can easily detect inconsistencies.

We have three sets of control variables in our regression analyses. First, we control for the borrower's personal characteristics, including the borrower's age (*Age*), occupation, and residential address by province. Well-established prior studies show that the demographic characteristics and occupations of Chinese households are related to the credit risk of their borrowing (e.g., Deng, Zheng, and Ling, 2005; Chen, Jiang, and Liu, 2018). In addition, some studies also find that lenders are sensitive to the geographical information of borrowers, which is manifested as local bias (Jiang, Liu, and Lu, 2020; Lin and Viswanathan, 2016) or regional discrimination (Wang, Zhao, and Shen, 2021; Jin, Yin, and Chen, 2021).

Second, we control for the availability of the borrower's additional information. When the borrower registers on the platform, she can voluntarily disclose some personal information, such as her credit report, identity card number, phone number, and face recognition, to increase the level of credit rating assigned by the platform. Then, the personal information would be verified by the platform. We create the four dummy variables:1) *Credit Report* is a dummy variable that is equal to one if the borrower provides a certified credit report and zero otherwise; 2) *Identity* is a dummy variable that is equal to one if the borrower provides a certified identity card and zero otherwise; 3) *Phone Number* is a dummy variable that is equal to one if the borrower provides a certified phone number and zero otherwise; and 4) *Face Recognition* is a dummy variable that is equal to one if the borrower provides face recognition information and zero otherwise.

Third, we control for loan characteristics, including the loan amount (*Loan Amount*) and the loan maturity (*Loan Term*). *Loan Amount* is the amount of the loan (thousand RMB) requested by the borrower, and *Loan Term* is the maturity of the loan (month) requested by the borrower. Some studies (e.g., Strahan, 1999) show that lenders could use these non-price terms in the loan's contracts as complements in dealing with borrower risk. For example, the loan size is a proxy of the total wealth of the borrower.

2.5 Descriptive statistics

Table 1 presents the summary statistics of the main variables used in our analyses. The average interest rate is approximately 13.64%. The credit rating in our sample narrows into "A" and "B" levels. A total of 33.12% and 48.94% of borrowers are rated as “A” and “B”, respectively. The average loan amount is approximately 3,000 RMB (approximately $460), and the average maturity is approximately ten months. Fewer than 10% of borrowers disclose their credit reports, identities, and face information to the platform.

Only 11.5% of the loan applications are originated after listing, and 3.3% of the loan applications are withdrawn within one week. A total of 11.5% (6.8%) of issued loans in our sample are delinquent for more than 30 (90) days, suggesting that loans on the platform are risky.

[Insert Table 1 here]

Given that our research focuses on the differential impact of the introduction of machine learning algorithms on female and male borrowers, we split the sample based on gender and compare the borrower and loan characteristics in Panel A of Table 2. The average interest rate for female borrowers is significantly higher than that of male borrowers. The difference in interest rates between the two types of borrowers is 3.8% of the sample mean. To some extent, other borrower and loan characteristics also differ. Female borrowers are slightly younger than male borrowers. They usually require more credit to support in a relatively shorter period. Female borrowers are less likely to provide credit reports and phone numbers. However, a higher proportion of female borrowers complete the identity and face recognition on the platform. Table 2 reports the economic significance of the difference between the two groups, suggesting that male and female borrowers differ slightly from each other in terms of *loan amount, credit report, identity, and face recognition*.

To make the two groups of borrowers comparable, we use the propensity score matching (PSM) method to construct our matched sample. In particular, we match borrowers’ characteristics, including *Age*, occupation fixed effects, and residential province fixed effects, loan characteristics, including *Loan Amount* and *Loan Term*, and whether the borrower provides additional information, including *Credit Report*, *Identity*, *Phone Number*, and *Face Recognition*. We also control for the hour and date fixed effects of each loan application in the propensity score estimation.

The summary statistics of the matched sample are presented in Panel B of Table 2. As expected, all other borrower and loan characteristics are similar between the matched female and male borrowers except for the interest rates. We perform the robustness test using the matched sample in Section 3.3.3.

[Insert Table 2 here]

3 Gender discrimination in interest rates after using the machine learning-based system

3.1 Univariate DID test

As a preliminary analysis, we perform the univariate DID test. The results are presented in Table 3. First, after the adoption of the machine learning-based system, the average interest rate provided to male borrowers decreases from 14.026% to 13.341%. Similarly, the interest rate for female borrowers also decreases from 14.251% to 14.014%. The *t*-test indicates that these reductions are significant for both female and male borrowers. Over our sample period, the rising competition in the Chinese P2P market decreases the interest cost for both female and male borrowers.

We then test whether the changes in interest rates are different between male and female borrowers. Column (7) shows that the change in interest rates for female borrowers before and after using the new system is 0.449% larger than that for male borrowers. This result is also significant at the 1% level.

Overall, our univariate test illustrates that after switching from the manual system to the machine learning-based system, the average interest rate for female borrowers increases by 0.449% relative to that for male borrowers in our sample.

[Insert Table 3 here]

3.2 Multivariate DID analysis

We then examine whether switching from the manual to the machine learning-based system increases or decreases discrimination against female borrowers using a multivariate DID analysis. We first focus on the interest rates assigned to loan applications by the platform using the following DID regression specification:

$$Interest\ Rate_{i,t} = \alpha_t + \alpha_h + \beta Female_i \times Post_t + \gamma X_i + \delta Z_i + \varepsilon_{i,t},$$

where $Interest\ Rate_{i,t}$ is the interest rate assigned by the platform to borrower i at time t; $Female_i$ is a dummy variable that is equal to one if the borrower is female, zero otherwise; and $Post_t$ is a dummy variable that is equal to one if the loan application is listed after using the machine learning-based system, March 24, 2015 and is zero otherwise.

Under this specification, the DID coefficient estimate β captures the differential impact of adopting the machine learning-based system on female borrowers relative to male borrowers. We expect β to be significantly negative (positive) when adopting the machine learning-based system alleviates (increases) discrimination against female borrowers.

X_i denotes a vector of borrower and loan characteristics, including gender, age, occupation, province of residence, credit rating, loan amount, and loan maturity; Z_i denotes a vector of variables indicating whether borrowers provide additional information to the platform, including the certified credit report, identity card, phone number, and face recognition; α_t and α_h are date and hour fixed effects.

The estimation results are presented in Table 4. We do not control for the additional information of borrowers provided to the platform and credit ratings in Column (1). In particular, credit ratings are simultaneously assigned by the platform and could therefore be endogenous. The DID coefficient estimate is 0.446% and significant at the 1% level, which accounts for an increase of 3.36% in the interest cost for female borrowers. Consider that the average amount of borrowing by female borrowers is approximately 3,516 RMB and the average loan term is approximately ten months. A female borrower incurs an additional cost of 13 RMB (approximately $2). It is approximately one-fifth of the average daily income of Chinese residents.[12] Female borrowers in our sample pay an extra 902,000 RMB (approximately $125,000) after using the machine learning-based system. This finding suggests that female borrowers suffer higher borrowing costs after using the machine learning-based system than male borrowers.

[Insert Table 4 here]

In Column (2), we control for the variables indicating whether borrowers provided additional information to the platform. The additional information could be important input parameters when the platform decides the credit rating and interest rate. The DID coefficient estimate remains positive and statistically significant.

We finally control for credit rating fixed effects in Column (3). Credit ratings are also assigned by the platform based on all the information the platform can access and therefore should be a sufficient statistic for credit risk. Nonetheless, we continue to find a positive and statistically significant DID coefficient estimate, suggesting that the machine learning-based system assigns higher interest rates for female borrowers relative to male borrowers with the same credit risk.

Our estimates also illustrate that the interest rate increases with the size of the loan and

[12] According to National Bureau of Statistics of China, the average disposable income of Chinese residents in 2015 is approximately 21,966 RMB. The average daily income is 60 RMB.

decreases with maturity. This is consistent with a normal yield curve pattern. In addition, our empirics show that borrowers who provide additional information are more likely to receive higher interest rates. This suggests that borrowers with higher default risk are more willing to provide additional information to convince both the platform and potential lenders of the success of funding.

3.3 Identification issues

3.3.1 Trend analysis

Although switching from the manual system to the machine learning-based system on the platform represents an exogenous shock to borrowers, it is still possible that the above results may just capture the changing trend in the riskiness of female and male borrowers. To mitigate this concern, we follow Bertrand and Mullainathan (2003) and Atanassov (2013) and conduct a trend analysis around the transition date.

If our baseline results are driven by the changing trend, the effect is likely to appear before the transition date. Specifically, we estimate the following specification:

$$Interest\ Rate_{i,t} = a_t + \alpha_h + \sum_{\tau=-11}^{\tau=8} \delta_\tau d_\tau \times Female_i + \gamma X_i + \delta Z_i + \varepsilon_{i,t},$$

where d_τ is a dummy variable that is equal to one if the loan application is listed $|\tau|$ months before (if $\tau < 0$) or after (if $\tau > 0$) March 24th, 2015, when the machine learning-based system is launched, and is zero otherwise. The coefficients δ_τ's capture the changing differences in interest rates assigned to female and male borrowers by the platform.

We plot the coefficient estimates and their confidence intervals in Figure 4. The coefficient estimates before March 2015 are all close to zero and statistically insignificant, suggesting that the interest rate differences between female and male borrowers do not change before the transition. In contrast, the coefficient estimates become positive and statistically significant after March 2015.

Interestingly, we also find that the magnitudes of the coefficients increase monotonically by month for five months after the adoption of the machine learning-based system. This may reflect that the new system could adaptively adjust its pricing model based on historical information about female and male borrowers.

[Insert Figure 4 here]

During the first two months after March 2015, the interest rate gap between male and female borrowers is still consistent with that before the adoption of the new system. This suggests that the initial setting of the machine learning-based system follows the guidelines of the manual ratings. However, the wedge of interest rates becomes significant after three months, which is when the machine learning-based system has accumulated enough information. The interest rate gap between female and male borrowers increases by 1% half a year after the adoption of the new system and remains stable.

Overall, the trend analysis results suggest that the discrimination effect on female borrowers is less likely to be driven by the changing trend but rather by the transition to the machine learning-based system.

3.3.2 Borrower fixed effects

One may raise the concern that female and male borrowers could have different reactions to the transition from the manual system to the machine learning-based system. For example, if more low-risk female borrowers leave the platform relative to low-risk male borrowers because of the transition, then we expect to see interest rates for female borrowers to increase.

To mitigate this concern, we focus on the sample of repeated borrowers. These borrowers make multiple attempts to borrow from the platform, and thus, we can include borrower fixed effects to control for time-invariant borrower characteristics. In our data, 37.07% of borrowers apply for loans multiple times on the platform. On average, each borrower submits 1.68 applications in two years. In the analysis, we do not include borrowers' characteristics and the availability dummies of borrowers' additional information, which are subsumed by borrower fixed effects.

The results of repeated borrowers are presented in Table 5. Column (1) uses the sample of repeated borrowers without controlling for credit rating fixed effects, and Column (2) adds credit rating fixed effects. In both columns, the DID coefficient estimates are positive and statistically significant. After the adoption of a machine learning-based system, the interest rate gap between female and male borrowers increases by approximately 0.33% in absolute value or a 2.42% increase relative to the average interest cost.

[Insert Table 5 here]

Columns (3) and (4) repeat the estimation in Columns (1) and (2) using the same sample except excluding loan applications whose borrowers successfully borrowed in the platform before.

If the borrower had a successful borrowing history, then lenders could rely more on the historical repayment record rather than other information. The results are still consistent, suggesting that our baseline results are less likely to be driven by the changing composition of female and male borrowers.

3.3.3 Propensity score matching

Given that we do not observe the counterfactual outcome of female borrowers, we are unable to compare the outcome differences of choices in the same female borrower to evaluate the impact of switching from the manual system to the machine learning-based system. Thus, presumably we must select a male borrower identical to a given female borrower.

One may argue that female borrowers substantially differ from male borrowers, although this possibility is small given the summary statistics of female and male borrowers. If this possibility holds, then the impact of the machine learning-based system shown in the DID estimation may be due to the omitted observable differences between female and male borrowers.

To mitigate this concern, we conduct a PSM exercise. Specifically, we match borrowers' characteristics, including *Age*, occupation, and residential province fixed effects, and loan characteristics, including *Loan Amount* and *Loan Term*, and whether borrowers provide additional information, including *Credit Report*, *Identity*, *Phone Number*, and *Face Recognition*. Furthermore, we also control for the hour and date fixed effects of each loan application in the propensity score estimation.

The summary statistics in Panel B of Table 2 show that the distributions of borrower and loan characteristics are similar between male and female borrowers in our matched sample. We then re-estimate our baseline regressions in the matched sample and report the results in Table 6.

[Insert Table 6 here]

The coefficient estimates on the interaction terms are all positive and statistically significant, with and without controlling for credit rating fixed effects. The magnitudes of the coefficient estimates are even greater than those in Table 3. After the transition to the machine learning-based system, the interest rates of female borrowers increased by 0.428% annually relative to male borrowers. The interest rates of female borrowers are approximately 3.15% of the average interest cost in our sample.

3.3.4 Placebo tests

It is still plausible that our DID analysis results are driven by chance. To address this possibility, we conduct two placebo tests. First, we randomly select 12.6% of borrowers, the same as the ratio of female borrowers to our sample and assign them as pseudo female borrowers. Then, we re-estimate our baseline regressions on the pseudo sample.

After repeating 1,000 rounds of the above procedures, we plot the density of the coefficient estimates on the interaction term in Panel A of Figure 5. The mean and median of these coefficient estimates are close to zero. Importantly, the standard deviation of these coefficients is approximately 0.027. Most of the coefficients in the pseudo regressions are between -0.1 and 0.1. The coefficient on the interaction term in our baseline specification is 0.231 in Column (3) of Table 4, more than nine standard deviations away from the mean, suggesting that our results are less likely to be driven by chance.

Second, we randomly redistribute the loan applications in our sample to different dates within the sample period. Then, we update the time-related variables used in our regressions based on the newly assigned application date and re-estimate our model. Similarly, we also repeat 1,000 rounds of the above procedures and plot the density of the coefficient estimates on the interaction term in Panel B of Figure 5. Most of the coefficients in the pseudo regressions are also very close to zero. The standard deviation of these coefficients is approximately 0.03, and the coefficient in our baseline specifications is 7.8 standard deviations away from the mean. This implies that our findings are less likely to be an occurrence.

[Insert Figure 5 Here]

3.3.5 Subsample tests

We also conduct our baseline regressions in different subsamples to check whether our results are robust among different types of borrowers. First, we divided our sample into three subsamples based on borrowers' locations because economic geography often divides China into eastern, central, and western regions. Eastern China is organized by ten coastal provinces and is the most developed region. The central region is less developed than the eastern region. The western region is sparsely populated and its economy is far behind that of the coastal provinces. Presumably, borrowers from different parts of China have different economic backgrounds and could receive different interest rates from the platform. The results of our estimates are shown in Columns (1), (2), and (3) of Table 7 for different subsamples. Our results indicate that female borrowers are more likely to receive higher interest rates than male borrowers after using the machine learning-based system regardless of region.

We also divide our sample based on the age of borrowers. Column (4) presents the results for borrowers who are younger than (or equal to) 26 years old, and Column (5) shows the estimates for borrowers who are older than 26 years old. The coefficients on the DID term in both columns are significant and positive. Interestingly, the magnitude of the coefficient in Column (5) is significantly larger than that in Column (4). This suggests that our findings are more pronounced for older borrowers. This means that gender differences, such as sensitivity to price, are even more significant among older cohorts. Thus, relatively older female borrowers are more likely to be assigned higher interest rates than male borrowers after the adoption of the machine learning-based system.

[Insert Table 7 here]

4 Additional tests

4.1 Economic channel

In this section, we try to understand why the machine learning-based system assigns higher interest rates to female borrowers. We start with an investigation of the objective of the platform. Like other P2P lending platforms, the platform generates revenue from origination and servicing fees imposed on successful loan originations. As such, the platform has a strong incentive to maximize the total number of loans originated, which will be determined by both the demand side (the borrowers) and the supply side (the lenders).

On the demand side, if the platform assigns a high interest rate, then the borrower could withdraw her application, especially if she is sensitive to the cost of borrowing. On the supply side, potential lenders are more likely to fund loan applications with a higher interest rate and a better credit rating. In a perfectly competitive market, lenders break even, and the equilibrium interest rate will be determined by the credit risk of borrowers.

However, in a world with financial frictions that impede credit access, the platform could take advantage of vulnerable borrowers who either do not have access to alternatives or who are not sensitive to borrowing costs. If the machine learning-based system can identify such vulnerable borrowers, then it will take advantage of the information and charge these borrowers higher interest rates.

Some literature indicates that women are more likely to accept the listed price instead of bargaining or negotiation. As a result, women receive a low return on investment and a high purchase price (e.g., Ayres and Siegelman, 1995; List, 2004; Leibbrandt and List, 2015; Goldsmith-Pinkham and Shue, 2022). If female borrowers are more subject to these financial frictions, then they are more likely to be charged higher interest rates than their male counterparts.

4.1.1 Sensitivity to the borrowing cost

Directly measuring the sensitivity to borrowing costs is difficult. We take advantage of the unique feature of the platform to infer the sensitivity. The platform allows borrowers to withdraw their applications after seeing the interest rates assigned by the platform at any time until the application is fully funded. For borrowers less sensitive to the cost of borrowing, their withdrawal decisions are supposed to depend less on the assigned interest rates.

We first examine whether female borrowers are less sensitive to the borrowing cost with the following specification:

$$Withdrawn_{i,t} = \alpha_t + \alpha_h + \beta Female_i \times Interest\ Rate_{i,t} + \gamma X_i + \delta Z_i + \varepsilon_{i,t},$$

where $Withdrawn_{i,t}$ is a dummy variable that is equal to one if the loan application by borrower i at time t is withdrawn and is zero otherwise. The term α_t is the date fixed effects of borrowing, and α_h is the hour fixed effects of borrowing over one day. Both control the time variation of loan applications. The coefficient β captures the differential impact of interest rates on the withdrawal decisions of female borrowers relative to male borrowers.

The estimation results are presented in Table 8. Column (1) only controls for borrowers' and loan characteristics; Column (2) adds the additional credit information of borrowers; and Column (3) further controls for borrowers' credit ratings in the regression. The coefficient estimates on interest rates are all positive and statistically significant, suggesting that borrowers are more likely to withdraw their applications when the assigned interest rates are high.

[Insert Table 8 here]

Importantly, consistent with our conjecture, the coefficient estimates on the interaction term between the female dummy and the interest rate are all negative and statistically significant, suggesting that female borrowers are indeed less sensitive to the assigned interest rates. A one-percentage increase in the interest rate would lead to a 0.14% increase in the probability of withdrawing the loan application from male borrowers and only a 0.03% increase for female borrowers. Accordingly, the machine learning-based system may take advantage of this finding and charge higher interest rates on female borrowers.

4.1.2 Success rate

The platform's objective in exploiting female borrowers' insensitivity to interest rates is to increase the approval rates of loan applications submitted by female borrowers because more potential lenders would be attracted to the higher interest rates on the loans for female borrowers relative to similar loans for male borrowers.

To close the loop on our understanding of why the machine learning-based system assigns higher interest rates to female borrowers, we estimate the following specification:

$$Funded_{i,t} = \alpha_t + \alpha_h + \beta Female_i \times Post_t + \gamma X_i + \delta Z_i + \varepsilon_{i,t},$$

where $Funded_{i,t}$ is a dummy variable that is equal to one if borrower i at time t successfully receives a loan on the platform and is zero otherwise.

The regression results are presented in Table 9. At first, we do not control for interest rates in Column (1). The coefficient estimates on $Female_i \times Post_t$ are positive and significant, suggesting that the loans of female borrowers are more likely to be successfully funded after the adoption of the machine learning-based system. Our estimates show that the probability of successful borrowing by female borrowers increases by 2.4% relative to male borrowers after switching from the manual system to the machine learning-based system.

[Insert Table 9 here]

In Column (2), we control for interest rates. The coefficients on interest rates are positive and significant in each column, suggesting that loan applications with higher interest rates are more likely to be funded. A one-percentage increase in the interest rate would increase the probability of successfully borrowing for first-time borrowers by 6% in our sample. Interestingly, the magnitude of the coefficient estimates on the interaction term becomes much smaller, suggesting that the increases in approval rates of female borrowers are mainly driven by the increases in the assigned interest.

Overall, our results are consistent with the platform's incentive to increase the number of loans originated by assigning higher interest rates to borrowers less sensitive to the cost of borrowing.

4.2 Alternative explanations

4.2.1 Credit ratings

It is still plausible that some unobservable borrower characteristics drive the time-series variation in female and male borrowers' risk profiles. In such cases, the platform assigns higher interest rates to female borrowers relative to male borrowers, which accommodates the lower crediting ratings of female borrowers.

Moreover, some studies have shown that the machine learning-based credit rating system indeed improves the predictive performance when compared to more "traditional" approaches (e.g., Khandani, Kim, and Lo, 2010; Gambacorta et al., 2019; Sadhwani, Giesecke, and Sirignano, 2021; Fuster et al., 2022), although the size of improvement may vary across applications. Thus, the adoption of the machine leaning-based system could improve the credit rating system in our sample and provide different rating scores for male and female borrowers.

To test this possibility, we examine whether the credit ratings assigned by the platform also change after switching from the manual system to the machine learning-based system. If the increases in interest rates for female borrowers are driven by the increases in their credit risk, we should observe a decrease in credit ratings for female borrowers. Specifically, we run the DID specification as follows:

$$Credit\ Rating_{i,t} = \alpha_t + \alpha_h + \beta Female_i \times Post_t + \gamma X_i + \delta Z_i + \varepsilon_{i,t},$$

where $Credit\ Rating_{i,t}$ is the credit rating for borrower i at time t. In our estimation, we use one to six to represent the lowest rating "F" to the highest rating "A", and the higher the rating, the lower the credit risk.

The results are presented in Table 10. We first only control for borrower and loan characteristics in Column (1), and the coefficient estimates on $Female_i \times Post_t$ are positive and significant. In Column (2), we add the variables indicating whether borrowers provided additional information to the platform into the regression. The coefficient estimate on $Female_i \times Post_t$ is 0.210 and significant at the 1% level, suggesting that the credit rating of female borrowers increases after using the machine learning-based system. Furthermore, the interest rate is also controlled in Column (3). The coefficient estimates on the DID term are still positive and significant. This implies that the machine learning-based system is more likely to award a higher credit rating to female borrowers in our sample. This finding is inconsistent with the alternative explanation for the deterioration in female borrowers' credit quality.

[Insert Table 10 here]

Overall, we find that the machine learning-based system provides female borrowers with higher credit ratings relative to male borrowers. These results suggest that the increases in interest rates for female borrowers are less likely to be driven by changes in credit quality. Furthermore, the results for interest rates and credit ratings appear to contradict each other; the machine learning-based system provides female borrowers with better credit ratings but charges them higher interest rates. The seemingly contradictory results are likely to be explained by the revenue-maximizing motive of the platform discussed in Section 4.1.

4.2.2 Loan delinquency

The literature reports mixed evidence on comparing realized delinquency rates between fintech and human-based systems. Fuster et al. (2019) find lower delinquency rates for fintech-originated loans in the riskier Federal Housing Administration (FHA) segment. Jansen, Nguyen, and Shams (2021) document that the algorithmic underwriting system outperforms the human underwriting process if both human and machine systems receive the same set of information. In contrast, Berg (2015) shows that human loan officers can reduce loan default rates by 50% relative to a lending decision based purely on bank internal ratings. Costello et al. (2020) provide similar evidence, showing that a combination of machine and human intervention improves loan outcomes relative to the machine-based credit model. Thus, one could argue that the platform's credit ratings provided by the machine learning-based system may not truly reflect borrowers' actual risk.

To this end, we also examine loan performance to rule out the possibility that the increase in interest rates on female borrowers is driven by the increase in female borrowers' credit risk. In particular, we examine whether loans to female borrowers are more likely to experience delinquency after the transition with the following specification:

$$Delinquency_{i,t} = \alpha_t + \alpha_h + \beta Female_i \times Post_t + \gamma X_i + \delta Z_i + \varepsilon_{i,t},$$

where $Delinquency_{i,t}$ is a dummy variable equal to one if the loan application by borrower i at time t experiences delinquency and is zero otherwise. We again control for borrower and loan characteristics, additional credit information, and credit ratings.

[Insert Table 11 here]

We present the results in Table 11, with delinquencies defined as more than 90, 45, and 30 days overdue. The coefficient estimates on the interaction terms are all small and statistically insignificant, suggesting that the delinquency rates of female borrowers do not change significantly after transitioning to the machine learning-based system.

Furthermore, the coefficient estimates on *Female* are negative and significant, suggesting that, on average, female borrowers have lower default risk. If the machine learning-based system is employed only to more accurately assess the default risk, then the interest rates on female borrowers should decline.

4.2.3 Loan prepayment

Borrowers may prepay the loans that they obtain from the platform. Lenders will lose part of the interest revenue when borrowers exercise the prepayment option. As a result, the probability of prepayment is a critical pricing factor for mortgage loans (Schwartz and Torous, 1989) and auto loans (Heitfield and Sabarwal, 2004). In particular, prepayment behavior is more common in China and has been taken as the major risk factor for loan lenders (Deng, Zheng and Ling, 2005; Deng and Liu, 2009). If female borrowers in China are more likely to prepay for the loan after the transition, then a higher interest rate may be compensating for the prepayment risk for lenders.

To assess whether this is the case, we examine whether female borrowers are more likely to prepay after the transition:

$$Prepayment_{i,t} = \alpha_t + \alpha_h + \beta Female_i \times Post_t + \gamma X_i + \delta Z_i + \varepsilon_{i,t},$$

where $Prepayment_{i,t}$ is a dummy variable that is equal to one if the loan application by borrower i at time t prepays the loan and is zero otherwise. We again control for loan and borrower characteristics, additional credit information, and credit ratings.

[Insert Table 12 here]

Table 12 shows the results, with Columns (1)-(3) for prepayment of 90, 45, and 30 days before the maturity date. The coefficient estimates on the interaction term are all small and statistically insignificant, suggesting that the prepayment behavior of female borrowers does not change over time.

Moreover, the coefficient estimates on *Female* are all small and statistically insignificant, suggesting that female and male borrowers do not have significant differences in prepayment behaviors in our sample.

4.2.4 Lenders' preference

The supply of fintech lending has increased dramatically in recent years, particularly after the subprime crisis (Buchak et al., 2018; Gopal and Schnabl, 2022). The most prominent advantage of fintech lending compared to the traditional financial intermediation model is the investor-involved screening process (Vallee and Zeng, 2019). Lenders screen all loan applications listed on the platform and make investment decisions based on their own preferences. Supply-side factors could also impact borrowing on the platform. If the attitudes of lenders toward female and male borrowers change after the adoption of the machine learning-based system, our findings may be driven by these supply-side factors.

To this end, we test the lenders' behavior with the following specification:

$$LenderBid_{i,j,t} = \alpha_t + \alpha_h + \alpha_j + \beta Female_i \times Post_t + \gamma X_i + \delta Z_i + \varepsilon_{i,t},$$

where $LenderBid_{i,j,t}$ is the log value of the total investment pledged by lender j for the loan application by borrower i at time t; and α_j denotes lender fixed effects that allow us to control for the heterogeneity of lenders.

We present the results in Table 13. We do not control for lender fixed effects in Column (1) and control for them in Column (2). The coefficient estimates on the interaction term are all small and statistically insignificant, suggesting that lenders' attitudes concerning the gender of borrowers do not change before and after using the machine learning-based system, and our results tend not to be driven by supply-side factors.

[Insert Table 13 here]

4.3 Discrimination and social welfare

In this section, we discuss whether the social welfare of female borrowers increased after the transition. To summarize the findings above, our empirics illustrate that the adoption of the machine learning-based system increases the cost of debt for female borrowers (intensive margin); on the other hand, it assists them in better access to credit (extensive margin). To evaluate the change in social welfare, we estimate the cost of the additional credit.

Based on the estimates in Column (3) of Table 4, 0.231% of the additional interest rate is charged to female borrowers after controlling all other heterogeneity. Meanwhile, the probability of successful borrowing for female borrowers increases by 2.4% based on the estimates in Column (1) of Table 9. As a result, the cost of the additional loans on this platform is approximately 9% in our sample.

The magnitude of this cost is astonishing. Note that this cost is the extra payment added to the interest payment. In our sample, the average interest rate is approximately 13.6%. The interest rate of a one-year deposit is 1.75%, and the interest rate of a long-term bank loan is 5.4% in the same period in China. Importantly, this additional cost is not solely borne by the new borrowers but is equally distributed to all female borrowers. This outcome induced by the adoption of machine learning algorithms raises serious concerns about gender equity in the credit market.

5 Conclusion

Using a unique setting from a leading Chinese P2P platform, we find that the adoption of machine learning algorithms could deepen the gender gap in the credit market. Specifically, we find that the machine learning-based system can identify the preference differences among borrowers and then implement a price discrimination strategy that maximizes the profit of the platform. We also show that because female borrowers are less price-sensitive, the price discrimination strategy hurts female borrowers more than male borrowers.

Relative to the human-based system, the machine learning-based system increases the interest rates on female borrowers relative to male borrowers. At the same time, the fintech system also assigns better credit ratings to female borrowers relative to male borrowers.

Overall, our paper suggests that the efficiency gains brought by fintech could come at the plausible expense of equity and that the enhanced ability of technology could also result in more rent extraction by fintech lending platforms.

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Table 1. Summary statistics

This table reports the summary statistics of the variables for the number of observations (Count), mean (Mean), standard deviation (STD), the 25th (P25), median (P50), and 75th percentiles (P75) of the distributions of the variables in our sample. *Interest Rate* is the annual interest rate of the loan assigned by the platform. *Female* is a dummy variable equal to one if the borrower is female, and zero otherwise. *Age* is the age of the borrower. *Loan Amoun*t is the amount of the loan (thousand RMB) requested by the borrower. *Loan Term* is the maturity of the loan (month) requested by the borrower. *Credit Report* is a dummy variable equal to one if the borrower provides a certified credit report, and zero otherwise. *Identity* is a dummy variable equal to one if the borrower provides a certified identity card, and zero otherwise. *Phone Number* is a dummy variable equal to one if the borrower provides a certified phone number, and zero otherwise. *Face Recognition* is a dummy variable equal to one if the borrower provides face recognition information, and zero otherwise. *Funded* is a dummy variable equal to one if the borrower successfully receives the loan in the platform, and zero otherwise. *Withdrawn* is a dummy variable equal to one if the borrower withdraws the loan application with one week, and zero otherwise. $Delinquency_{30}$ is a dummy variable equal to one if the loan is overdue more than 30 days, and zero otherwise. $Delinquency_{45}$ is a dummy variable equal to one if the loan is overdue more than 45 days, and zero otherwise. $Delinquency_{90}$ is a dummy variable equal to one if the loan is overdue more than 90 days, and zero otherwise. $Prepayment_{30}$ is a dummy variable equal to one if the loan is prepaid at least 30 days before the maturity date, and zero otherwise. $Prepayment_{45}$ is a dummy variable equal to one if the loan is prepaid at least 45 days before the maturity date, and zero otherwise. $Prepayment_{90}$ is a dummy variable equal to one if the loan is prepaid at least 90 days before the maturity date, and zero otherwise.

	Count	Mean	STD	P25	P50	P75
Interest Rate	548,039	13.642	3.580	12	12	13
Female	548,039	0.126	0.332	0	0	0
Age	548,039	27.605	6.250	23	26	31
Loan Amount	548,039	3.058	8.988	1	3	3
Loan Term	548,039	10.305	2.532	7	12	12
Credit Report	548,039	0.024	0.152	0	0	0
Identity	548,039	0.026	0.160	0	0	0
Phone Number	548,039	0.754	0.431	1	1	1
Face Recognition	548,039	0.099	0.298	0	0	0
Funded	529,860	0.115	0.319	0	0	0
Withdrawn	548,039	0.033	0.179	0	0	0
$Delinquency_{30}$	36,145	0.115	0.318	0	0	0
$Delinquency_{45}$	36,145	0.090	0.287	0	0	0
$Delinquency_{90}$	36,145	0.068	0.251	0	0	0
$Prepayment_{30}$	36,145	0.199	0.399	0	0	0
$Prepayment_{45}$	36,145	0.118	0.322	0	0	0
$Prepayment_{90}$	36,145	0.051	0.220	0	0	0

Table 2. Comparing female and male borrowers

This table compares female and male borrowers. The definitions of variables are in the notes of Table 1. Their differences are calculated as the difference of the variables between female and male borrowers over the mean of the full sample. Both the values and their *t*-statistics are reported in the last two columns. Panel A includes the full sample and panel B only considers the matched sample generated from a propensity score matching between female and male borrowers. Significance at the 1% level is indicated by ***.

	Female borrowers		Male borrowers			
	Mean	STD	Mean	STD	difference	*t*-statistics
Interest Rate	14.101	3.851	13.576	3.534	0.038***	36.07
Age	27.376	6.520	27.637	6.209	-0.009**	-10.26
Loan Amount	3.516	11.602	2.992	8.543	0.161***	14.33
Loan Term	10.057	2.560	10.341	2.526	-0.028***	-27.51
Credit Report	0.018	0.134	0.025	0.155	-0.296***	-10.24
Identity	0.031	0.174	0.026	0.158	0.195***	8.48
Phone Number	0.711	0.453	0.760	0.427	-0.067***	-28.06
Face Recognition	0.138	0.345	0.093	0.291	0.389***	37.03
Observations	69,037		479,002			
Interest Rate	14.101	3.851	13.652	3.607	0.032***	22.36
Age	27.377	6.520	27.372	6.211	0.000	0.12
Loan Amount	3.516	11.602	3.451	13.305	0.019	0.98
Loan Term	10.057	2.560	10.045	2.625	0.001	0.86
Credit Report	0.018	0.134	0.019	0.138	-0.056	-1.43
Identity	0.031	0.174	0.031	0.174	-0.009	-0.31
Phone Number	0.711	0.453	0.712	0.453	-0.001	-0.28
Face Recognition	0.138	0.345	0.138	0.345	-0.003	-0.23
Observations	69,037		69,037			

Table 3. Univariate test

This table presents the univariate test of the interest rate (in percentage) between female and male borrowers before and after the adoption of the machine learning-based system. Column (1) and (2) reports the statistics of interest rates for male borrowers before and after the adoption of the machine learning-based system, and Column (4) and (5) reports the statistics of interest rates for female borrowers before and after the adoption of machine learning-based system. Column (3) and (6) present the change in interest rates after the adoption of machine learning-based system for male and female borrowers, respectively. Column (7) shows the difference between Column (3) and (6). *t*-statistics are reported in parentheses. Significance at the 1% level is indicated by ***.

	(1)	(2)	(3) = (2)-(1)	(4)	(5)	(6) = (5)-(4)	(7) = (6)-(3)
	Male borrowers			Female borrowers			
	Before	After	Difference	Before	After	Difference	Difference in Difference
Mean	14.026	13.341	-0.685***	14.251	14.014	-0.236***	**0.449*****
Std. Dev.	3.604	3.474	(-63.23)	3.845	3.852	(-8.41)	**(14.49)**
Obs.	164,573	314,429		25,416	43,621		

Table 4. Adoption of the machine learning-based system and interest rates

This table presents the estimation results of the baseline DID specification of the effect of the adoption of the machine learning-based system on interest rates. The dependent variable, *Interest Rate,* is the interest rate on the loan application assigned by the platform. The key independent variable is the interaction term between *Female* and *Post*. *Female* is a dummy variable equal to one if the borrower is female; and zero otherwise. *Post* is a dummy variable equal to one if the loan application is listed after adopting the machine learning-based system in the platform, March 24th, 2015; and zero otherwise. Standard errors are clustered by month and reported in parentheses. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	(1)	(2)	(3)
Post×Female	**0.446*** **	**0.464*** **	**0.231*** **
	(0.147)	**(0.146)**	**(0.073)**
Female	0.149***	0.171***	-0.213**
	(0.042)	(0.044)	(0.076)
Age	0.006	0.000	-0.011***
	(0.006)	(0.004)	(0.003)
Loan Amount	0.031***	0.029***	0.015***
	(0.010)	(0.010)	(0.005)
Loan Term	-0.146***	-0.149***	-0.128***
	(0.039)	(0.037)	(0.038)
Credit Report		0.277***	0.663***
		(0.090)	(0.159)
Identity		0.706***	0.765***
		(0.075)	(0.082)
Phone Number		0.857***	0.830***
		(0.156)	(0.206)
Face Recognition		0.406***	0.450***
		(0.128)	(0.096)
Credit Rating Fixed Effects	No	No	Yes
Occupation Fixed Effects	Yes	Yes	Yes
Province Fixed Effects	Yes	Yes	Yes
Hour Fixed Effects	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes
Observations	548,039	548,039	548,039
R-squared	0.122	0.131	0.284

Table 5. Repeated borrowers

This table presents the baseline DID specification for repeated borrowers. The dependent variable, *Interest Rate,* is the interest rate of the loan application. The key independent variable is the interaction term between *Female* and *Post. Female* is a dummy variable equal to one if the borrower is female; zero otherwise. *Post* is a dummy variable equal to one if the loan application is listed after adopting the machine learning-based system on the platform, March 24th, 2015. Columns (1) and (2) use the full sample of repeated borrowers; Columns (3) and (4) use the sample of repeated borrowers who do no successfully borrow money on the platform. Standard errors reported in parentheses are clustered by month and borrower. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)
Post×Female	**0.133****	**0.159*****	**0.333*****	**0.208*****
	(0.056)	**(0.052)**	**(0.074)**	**(0.061)**
Loan Amount	0.009***	0.008***	0.017***	0.007***
	(0.001)	(0.001)	(0.003)	(0.002)
Loan Term	-0.252***	-0.241***	-0.354***	-0.344***
	(0.025)	(0.025)	(0.038)	(0.039)
Credit Rating Fixed Effects	No	Yes	No	Yes
Hour Fixed Effects	Yes	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes	Yes
Borrower Fixed Effects	Yes	Yes	Yes	Yes
Observations	712,332	712,332	523,542	523,542
R-squared	0.691	0.710	0.570	0.588

Table 6. Matched sample using the PSM method

This table presents the baseline DID specification for the interest rate in the matched sample. The dependent variable, *Interest Rate,* is the interest rate of the loan application. The key independent variable is the interaction term between *Female* and *Post. Female* is a dummy variable equal to one if the borrower is female; zero otherwise. *Post* is a dummy variable equal to one if the loan application is listed after using the machine learning-based system in the platform, March 24th, 2015. Standard errors are clustered by month and reported in parentheses. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	(1)	(2)	(3)
Post×Female	**0.587*** **	**0.570*** **	**0.428*** **
	(0.164)	**(0.156)**	**(0.104)**
Female	0.075	0.086	-0.219**
	(0.049)	(0.050)	(0.097)
Age	0.000	-0.008**	-0.015***
	(0.005)	(0.003)	(0.003)
Loan Amount	0.017***	0.015***	0.010***
	(0.005)	(0.005)	(0.002)
Loan Term	-0.121**	-0.122**	-0.104**
	(0.046)	(0.044)	(0.045)
Credit Report		0.142*	0.464***
		(0.082)	(0.123)
Identity		0.738***	0.770***
		(0.072)	(0.087)
Phone Number		1.049***	0.840***
		(0.180)	(0.212)
Face Recognition		0.509***	0.487***
		(0.112)	(0.093)
Credit Rating Fixed Effects	No	No	Yes
Occupation Fixed Effects	Yes	Yes	Yes
Province Fixed Effects	Yes	Yes	Yes
Hour Fixed Effects	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes
Observations	138,074	138,074	138,074
R-squared	0.133	0.148	0.253

Table 7. Subsample tests

This table presents the estimation results of the baseline DID specification of the effect of adoption of the machine learning-based system on interest rates in subsamples. The dependent variable, *Interest Rate,* is the interest rate on the loan application assigned by the platform. The key independent variable is the interaction term between *Female* and *Post*. *Female* is a dummy variable equal to one if the borrower is female; and zero otherwise. *Post* is a dummy variable equal to one if the loan application is listed after adopting the machine learning-based system in the platform, March 24th, 2015; and zero otherwise. Each column reports the result of subsample for borrowers from east (Column 1), central (Column 2), and west (Column 3) regions of China, whose age is younger than 26 (Column 4), and whose age is older than 26 (Column 5), respectively. Standard errors are clustered by month and reported in parentheses. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	(1) East	(2) Central	(3) West	(4) Young	(5) Old
Post×Female	**0.296*** **	**0.232*** **	**0.196** **	**0.107* **	**0.421*** **
	(0.099)	**(0.077)**	**(0.073)**	**(0.060)**	**(0.107)**
Female	-0.214**	-0.255***	-0.194**	-0.083	-0.387***
	(0.091)	(0.083)	(0.079)	(0.063)	(0.093)
Age	-0.012***	-0.011***	-0.008***	-0.032***	-0.009***
	(0.003)	(0.003)	(0.003)	(0.009)	(0.003)
Loan Amount	0.011***	0.015***	0.033***	0.043**	0.010***
	(0.004)	(0.003)	(0.011)	(0.018)	(0.003)
Loan Term	-0.160***	-0.129***	-0.079	-0.102**	-0.171***
	(0.036)	(0.036)	(0.052)	(0.048)	(0.039)
Credit Report	0.596***	0.628***	0.800***	0.664***	0.650***
	(0.184)	(0.150)	(0.140)	(0.125)	(0.208)
Identity	0.792***	0.694***	0.809***	0.584***	0.923***
	(0.088)	(0.086)	(0.112)	(0.093)	(0.096)
Phone Number	0.816***	0.797***	0.885***	0.711***	0.948***
	(0.226)	(0.188)	(0.202)	(0.172)	(0.255)
Face Recognition	0.466***	0.433***	0.487***	0.491***	0.342***
	(0.098)	(0.091)	(0.113)	(0.124)	(0.062)
Credit Rating Fixed Effects	Yes	Yes	Yes	Yes	Yes
Occupation Fixed Effects	Yes	Yes	Yes	Yes	Yes
Province Fixed Effects	Yes	Yes	Yes	Yes	Yes
Hour Fixed Effects	Yes	Yes	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	215,911	184,823	147,311	286,588	261,460
R-squared	0.274	0.290	0.302	0.291	0.293

Table 8. Applications withdrawn

This table presents the sensitivity of application withdrawal with respect to assigned interest rate for borrowers before using the machine learning-based system on the platform, March 24th, 2015. The dependent variable *Withdrawn* is a dummy variable equal to one if the borrower withdraws the loan application within one week; zero otherwise. The key independent variable is the interaction term between *Female* and *Interest Rate. Female* is a dummy variable equal to one if the borrower is female; zero otherwise. *Interest Rate* is the annual interest rate of the loan assigned by the platform. Standard errors are clustered by month and reported in parentheses. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	(1)	(2)	(3)
Female×Interest Rate	**-0.110***	**-0.107***	**-0.097**
	(0.041)	**(0.040)**	**(0.040)**
Female	1.264**	1.242**	0.843
	(0.550)	(0.549)	(0.543)
Interest Rate	0.142***	0.105***	0.187***
	(0.019)	(0.019)	(0.019)
Age	-0.063***	-0.064***	-0.063***
	(0.006)	(0.006)	(0.006)
Loan Amount	-0.029***	-0.045***	-0.030***
	(0.003)	(0.003)	(0.003)
Loan Term	-0.011	0.002	0.018
	(0.019)	(0.019)	(0.019)
Credit Report		1.450***	0.877***
		(0.338)	(0.338)
Identity		4.052***	4.131***
		(0.303)	(0.300)
Phone Number		2.655***	4.051***
		(0.163)	(0.172)
Face Recognition		5.018***	5.352***
		(0.243)	(0.242)
Credit Rating Fixed Effects	No	No	Yes
Occupation Fixed Effects	Yes	Yes	Yes
Province Fixed Effects	Yes	Yes	Yes
Hour Fixed Effects	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes
Observations	189,986	189,986	189,986
R-squared	0.031	0.039	0.054

Table 9. Success rate

This table presents the difference-in-difference specification of successful borrowing. The dependent variable, *Funded,* is a dummy variable equal to one if the borrower successfully receives the loan in the platform; and zero otherwise. The key independent variable is the interaction term between *Female* and *Post*. *Female* is a dummy variable equal to one if the borrower is female; and zero otherwise. *Post* is a dummy variable equal to one if the loan application is listed after using the machine learning-based system in the platform, March 24th, 2015. Standard errors are clustered by month and reported in parentheses. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	(1)	(2)
Post×Female	**0.024*** **	**0.011** **
	(0.007)	**(0.005)**
Interest Rate		**0.060*** **
		(0.008)
Female	-0.037***	-0.024***
	(0.007)	(0.003)
Age	-0.001**	-0.000
	(0.000)	(0.000)
Loan Amount	0.004***	0.003***
	(0.000)	(0.000)
Loan Term	-0.001	0.006**
	(0.003)	(0.002)
Credit Report	0.072***	0.032***
	(0.016)	(0.006)
Identity	0.079***	0.033***
	(0.012)	(0.008)
Phone Number	0.104***	0.055***
	(0.024)	(0.010)
Face Recognition	0.044***	0.016**
	(0.012)	(0.006)
Credit Rating Fixed Effects	Yes	Yes
Occupation Fixed Effects	Yes	Yes
Province Fixed Effects	Yes	Yes
Hour Fixed Effects	Yes	Yes
Date Fixed Effects	Yes	Yes
Observations	529,860	529,860
R-squared	0.163	0.705

Table 10. Credit ratings

This table presents the difference-in-difference specification of credit rating. The dependent variable, *Credit Rating,* is the credit rating of the loan application. It is coded as 1 to 6 for credit rating F to A, with 1 indicating the worst credit rating and 6 indicating the best credit rating. The key independent variable is the interaction term between *Female* and *Post. Female* is a dummy variable equal to one if the borrower is female; zero otherwise. *Post* is a dummy variable equal to one if the loan application is listed after using the machine learning-based system in the platform, March 24th, 2015. Standard errors are clustered by month and reported in parentheses. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	(1)	(2)	(3)
Post×Female	**0.216*** **	**0.210*** **	**0.182*** **
	(0.048)	**(0.049)**	**(0.038)**
Female	0.315***	0.304***	0.294***
	(0.018)	(0.017)	(0.018)
Age	0.002*	0.004***	0.004***
	(0.001)	(0.001)	(0.001)
Loan Amount	0.016***	0.017***	0.015***
	(0.001)	(0.001)	(0.001)
Loan Term	-0.034***	-0.032***	-0.023***
	(0.007)	(0.007)	(0.007)
Credit Report		-0.145***	-0.161***
		(0.024)	(0.029)
Identity		-0.022	-0.064**
		(0.021)	(0.027)
Phone Number		-0.309***	-0.360***
		(0.012)	(0.027)
Face Recognition		-0.049**	-0.074***
		(0.023)	(0.022)
Interest Rate			0.060***
			(0.016)
Occupation Fixed Effects	Yes	Yes	Yes
Province Fixed Effects	Yes	Yes	Yes
Hour Fixed Effects	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes
Observations	548,039	548,039	548,039
R-squared	0.171	0.192	0.247

Table 11. Loan delinquency

This table presents the DID specification of loan performance for successful borrowers. The dependent variables are $Delinquency_{90}$, $Delinquency_{45}$, and $Delinquency_{30}$ in Columns (1), (2), and (3), respectively. The key independent variable is the interaction term between *Female* and *Post*. *Female* is a dummy variable equal to one if the borrower is female; zero otherwise. *Post* is a dummy variable equal to one if the loan application is listed after using the machine learning-based system in the platform, March 24th, 2015. Standard errors are clustered by month and reported in parentheses. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	(1)	(2)	(3)
	$Delinquency_{90}$	$Delinquency_{45}$	$Delinquency_{30}$
Post×Female	**0.019**	**0.019**	**0.019**
	(0.013)	**(0.012)**	**(0.013)**
Female	-0.026**	-0.025**	-0.028**
	(0.012)	(0.011)	(0.012)
Age	0.001***	0.000	0.000
	(0.000)	(0.000)	(0.000)
Loan Amount	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Loan Term	0.008***	0.010***	0.012***
	(0.001)	(0.001)	(0.001)
Credit Report	-0.017	-0.023*	-0.025**
	(0.010)	(0.013)	(0.009)
Identity	0.024**	0.030**	0.024**
	(0.010)	(0.011)	(0.011)
Phone Number	-0.014*	-0.015	-0.020*
	(0.008)	(0.010)	(0.011)
Face Recognition	0.007	0.010	0.014
	(0.008)	(0.009)	(0.009)
Credit Rating Fixed Effects	Yes	Yes	Yes
Occupation Fixed Effects	Yes	Yes	Yes
Province Fixed Effects	Yes	Yes	Yes
Hour Fixed Effects	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes
Observations	36,145	36,145	36,145
R-squared	0.075	0.075	0.072

Table 12. Loan prepayment

This table presents the DID specification of prepayment for borrowers. The dependent variables are $Prepayment_{90}$, $Prepayment_{45}$ and $Prepayment_{30}$ in Columns (1), (2), and (3), respectively. The key independent variable is the interaction term between *Female* and *Post*. *Female* is a dummy variable equal to one if the borrower is female; zero otherwise. *Post* is a dummy variable equal to one if the loan application is listed after using the machine learning-based system in the platform, March 24th, 2015. Standard errors are clustered by month and reported in parentheses. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

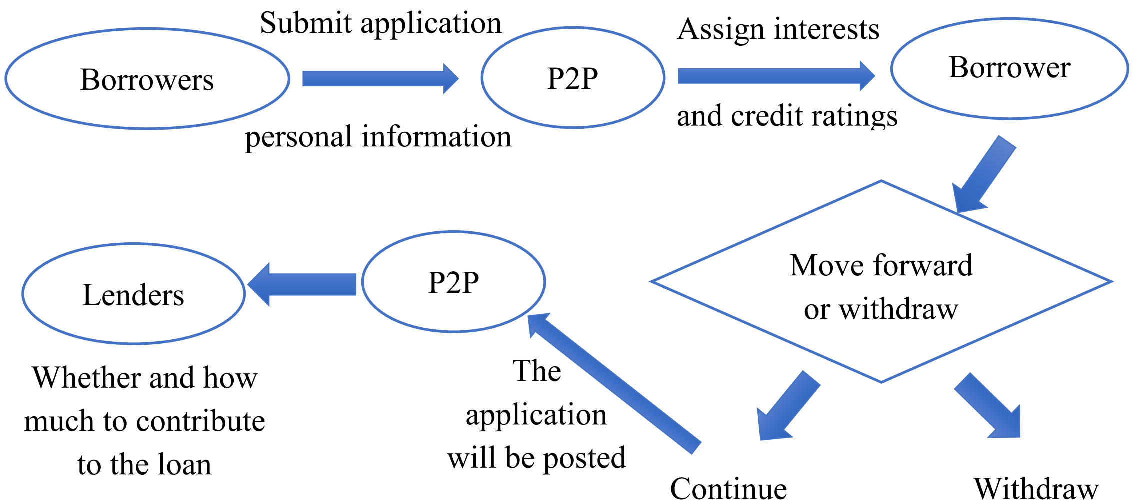
	(1)	(2)	(3)
	$Prepayment_{90}$	$Prepayment_{45}$	$Prepayment_{30}$
Post×Female	**0.003**	**0.010**	**0.011**
	(0.006)	**(0.010)**	**(0.015)**
Female	0.000	-0.001	0.003
	(0.003)	(0.006)	(0.012)
Age	-0.001***	-0.003***	-0.004***
	(0.000)	(0.000)	(0.000)
Loan Amount	-0.054	-0.122**	-0.224***
	(0.032)	(0.053)	(0.075)
Loan Term	0.002**	0.001	0.000
	(0.001)	(0.002)	(0.002)
Credit Report	0.023*	0.030	0.066**
	(0.012)	(0.020)	(0.030)
Identity	0.011	0.023***	0.026*
	(0.007)	(0.007)	(0.014)
Phone Number	-0.003	-0.013**	-0.019*
	(0.003)	(0.006)	(0.009)
Face Recognition	-0.002	-0.002	-0.009
	(0.006)	(0.011)	(0.009)
Credit Rating Fixed Effects	Yes	Yes	Yes
Occupation Fixed Effects	Yes	Yes	Yes
Province Fixed Effects	Yes	Yes	Yes
Hour Fixed Effects	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes
Observations	36,145	36,145	36,145
R-squared	0.028	0.042	0.054

Table 13. Lenders' preference

This table presents the DID specification for lender behavior. The dependent variable is the natural logarithm of the amount of the bid each lender submits for a loan application. The key independent variable is the interaction term between *Female* and *Post*. *Female* is a dummy variable equal to one if the borrower is female; zero otherwise. *Post* is a dummy variable equal to one if the loan application is listed after using the machine learning-based system in the platform, March 24th, 2015. Standard errors are clustered by month and reported in parentheses. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	(1)	(2)
Post×Female	**-0.009**	**-0.006**
	(0.006)	**(0.004)**
Female	0.003	0.007***
	(0.004)	(0.002)
Age	0.001*	0.000
	(0.000)	(0.000)
Interest Rate	0.027	0.003
	(0.023)	(0.003)
Loan Amount	0.001***	0.001***
	(0.000)	(0.000)
Loan Term	0.010	0.015***
	(0.009)	(0.002)
Credit Report	-0.025**	-0.016***
	(0.012)	(0.005)
Identity	0.018***	0.011***
	(0.004)	(0.002)
Phone Number	0.000	-0.010***
	(0.005)	(0.002)
Face Recognition	0.075***	0.061***
	(0.012)	(0.003)
Occupation Fixed Effects	Yes	Yes
Province Fixed Effects	Yes	Yes
Hour Fixed Effects	Yes	Yes
Date Fixed Effects	Yes	Yes
Lender Fixed Effects	No	Yes
Observations	4,595,261	4,578,572
R-squared	0.141	0.691

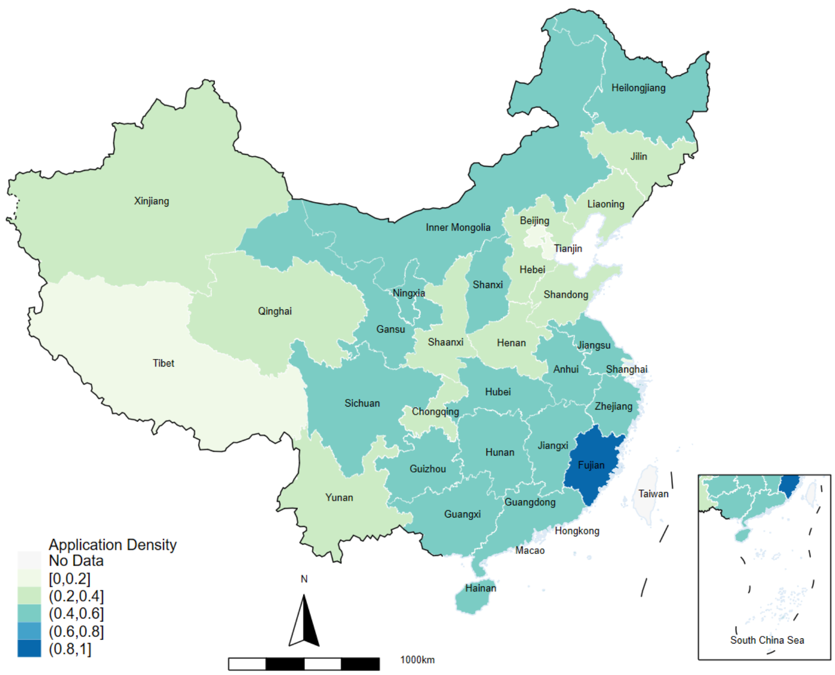
Figure 1. Process of loan applications



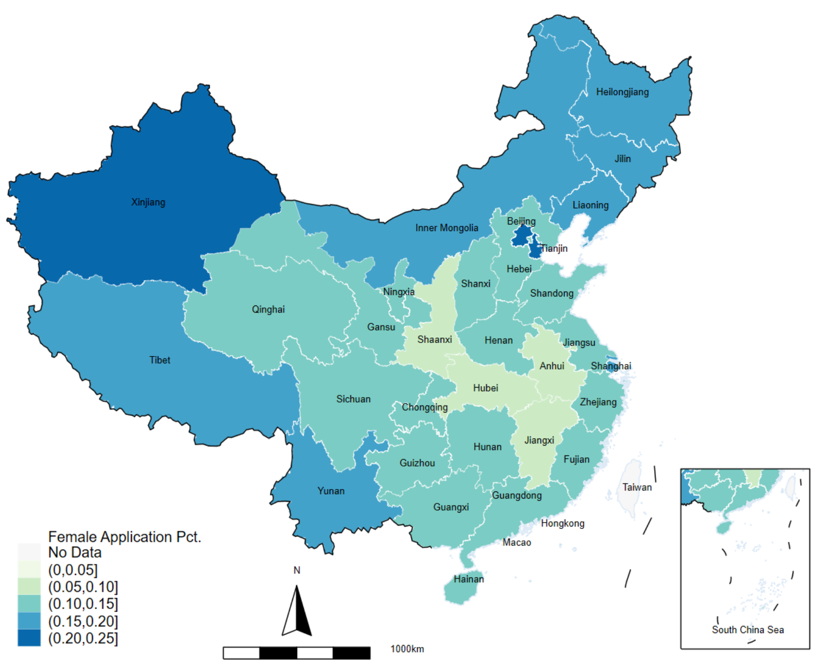
This figure illustrates the process of the loan application.

Figure 2. Geographical distribution of loan applications

Panel A. The density of application per 1,000 population



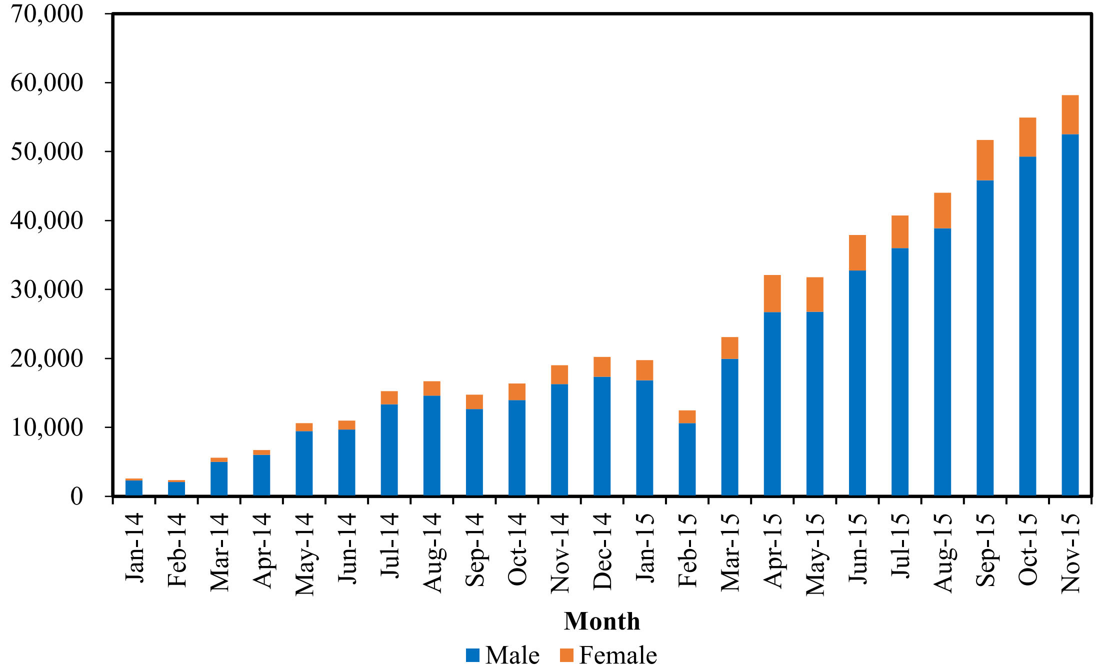
Panel B. The proportion of female application



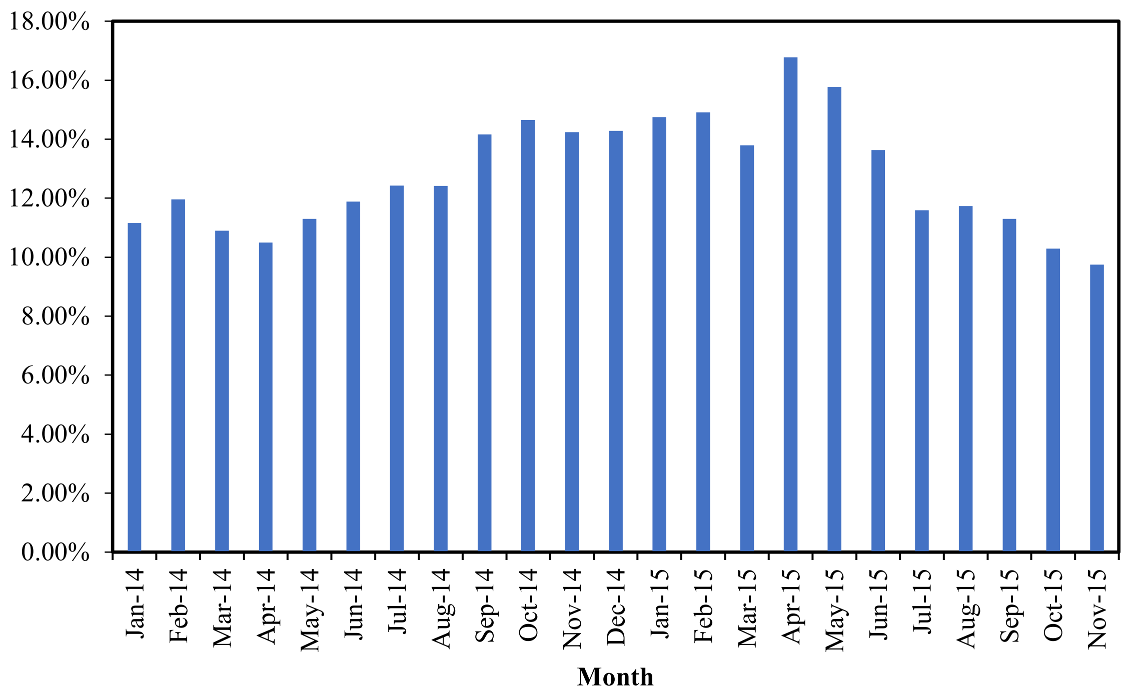
This figure shows the geographical distribution of loan applications in our sample. Panel A shows the density of applications per 1000 population, and Panel B illustrate the proportion of applications from female borrowers across different provinces.

Figure 3. Monthly number of loan applications

Panel A. Monthly number of loan applications

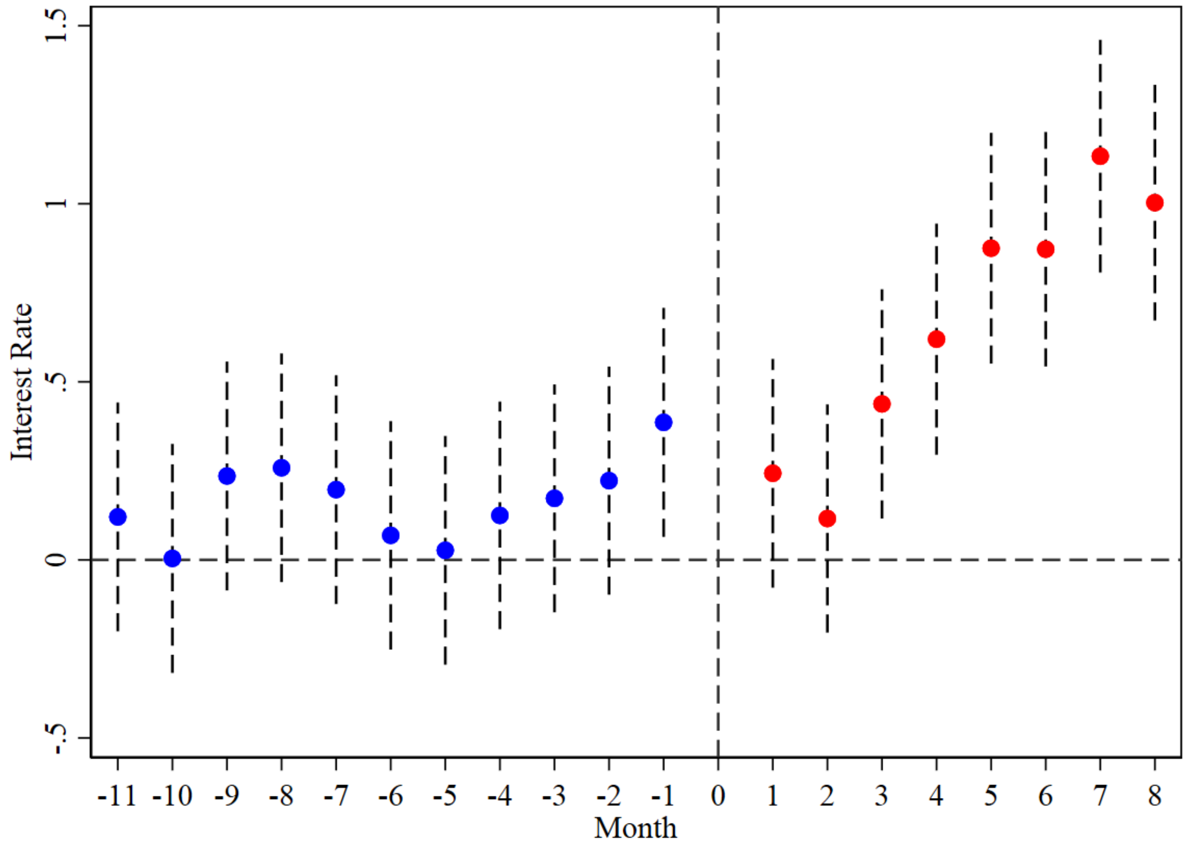


Panel B. Proportion of female borrowers' applications



This figure shows presents the monthly number of loan applications in Panel A and the monthly proportion of female borrowers' applications in Panel B.

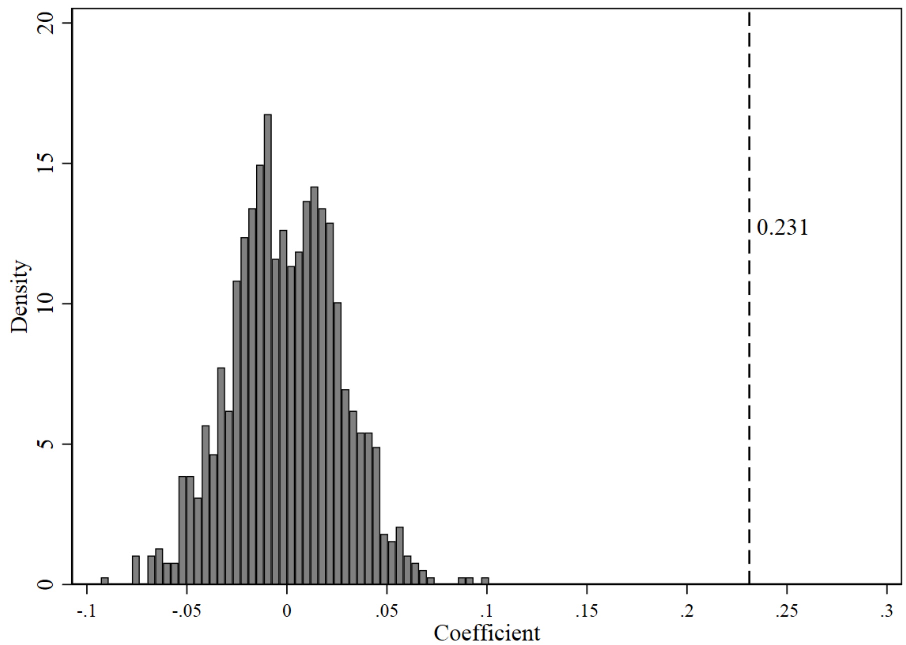
Figure 4. Trend analysis



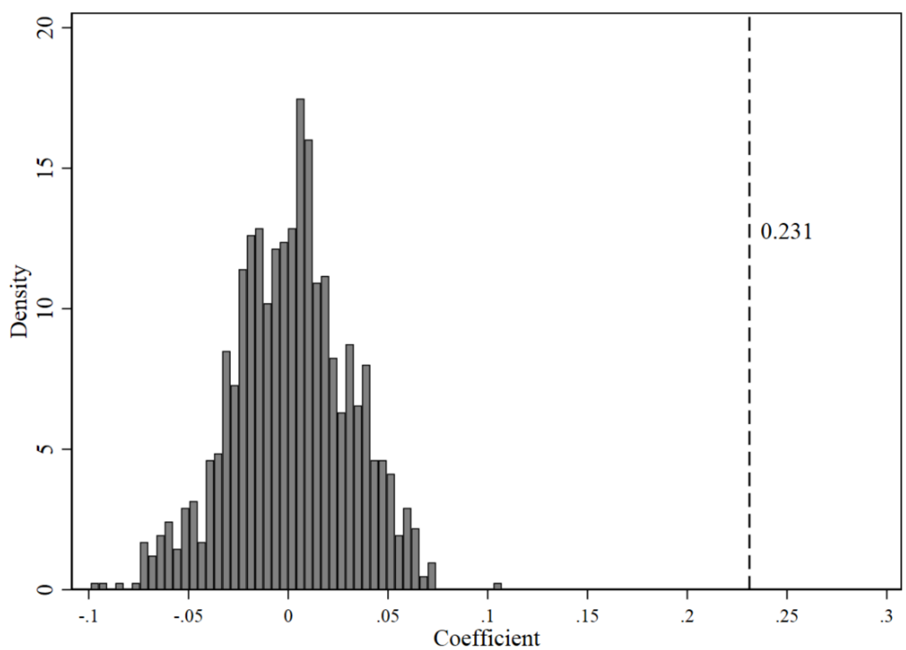
This figure plots the coefficient estimates δ_τ and their 95% confidential intervals of estimating $Rate_{i,t} = a_t + \sum_{\tau=-11}^{\tau=-1} \delta_\tau d_\tau \times Female_i + \sum_{\tau=1}^{\tau=8} \delta_\tau d_\tau \times Female_i + \gamma X_{i,t} + \varepsilon_{i,t}$. The dashed vertical line indicates the first month of using the machine learning-based system, i.e., March 24th, 2015.

Figure 5. Coefficient estimates in placebo tests

Panel A. Placebo tests for the gender of borrowers



Panel B. Placebo tests for the application date



This figure plots the density of the coefficient estimates from placebo tests. In Panel A, the pseudo female dummy is randomly assigned to 12.6% of the borrowers in our sample, and in panel B, the pseudo application date is randomly assigned from January 1, 2014 to November 30, 2015. The figure is plotted based on 1,000 repeated sampling. The dashed vertical line is the coefficient estimate obtained in the baseline sample.