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Female Small Business Owners in China: discouraged, not discriminated*

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Abstract

Using a unique small business loan application dataset from a peer-to-peer (P2P) digital loan platform in China, we show that female entrepreneurs are more likely to be discouraged from applying for funds after a failed attempt compared to their male counterparts. Female discouragement persists at different regional development levels and is prominent among those who need finance for working capital. Although digitization of financial markets has made external funding more accessible to small business owners, disclosing more information during the application process would help those discouraged from posting a new funding application.

Keywords: Peer-to-peer (P2P) lending; Small business owners; Gender discrimination; Discouraged borrowers; Repeat rejections; Fintech; Digitization; China.

JEL classification: G14, G32, M10

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1. Introduction

Access to external sources of finance is crucial for most small business owners. Small businesses require external funds to cover their fixed and working capital investment expenditures, develop new products and services, and cover their daily operational costs. To that end, earlier research has shown that small businesses led by females are particularly disadvantaged in accessing credit because of the size of their business, lack of financial sophistication, and possibly due to discrimination (Muravyev et al., 2009; Moro et al., 2017). Female business owners experience a higher rejection rate on loan applications (Blanchflower et al., 2003), face higher interest payments or requirements which are more restrictive compared to male entrepreneurs. (Alesina et al., 2013; Mascia and Rossi, 2017).

Furthermore, credit-constrained small business owners are discouraged from submitting a funding application for fear of rejection.[1] Hence, discouraged borrowers often rely on internal sources of finance which limit their investment and growth opportunities, while lenders lose good investment opportunities, resulting in inefficient allocation of capital (Gicheva and Link, 2015). Yet, due to data limitations, there are a few but powerful studies on borrower discouragement.[2]

In this study, different from the literature, scrutinizing data from a prominent peer-to-peer (P2P) loan platform in China and paying attention to the role of gender, we investigate whether small business borrowers are discouraged from applying for finance when using online lending platforms to raise funds. As Ughetto et al. (2019) put it, "the gender perspective has remained largely unexplored in a world that is becoming more technologically and digitally driven" (p. 307).

[1] Few women apply for debt capital (e.g., Moro et al., 2017;), as they tend to be more risk averse than men (Croson and Gneezy, 2009) and less confident about their ability to successfully obtain funding (Chaudhuri et al., 2018; Galli et al., 2020), rendering females to refrain from applying for loans more so than males (Carter et al., 2015).
[2] See, for instance, Han et al. (2009), Roper and Scott (2009) and Cole, R. and Sokolyk, T. (2016).

To carry our investigation, we examine the data from the viewpoint of both lenders and borrowers. We first look at the data from the perspective of small business borrowers (the demand side) to investigate if small business owners are discouraged from submitting a loan application given their earlier experiences with the platform. As we sift through the data, we highlight the borrower-specific and loan-specific factors that affect the approval of funding applications. Next, focusing on the lenders' behaviour (the supply side), we seek to answer whether i) lenders discriminate against applicants based on gender and ii) persistent applicants are eventually granted a loan.

Our investigation focuses on the relevance of gender and asks if female business owners are more likely to be discouraged than their male counterparts after experiencing one or more failed loan requests or they are discriminated against. We base the identification of discouraged borrowers on observed data. Our approach differs from the earlier research, which has exclusively depended on specialized surveys that asked the participants whether they have refrained from seeking external finance due to the belief that they could be turned down. Consequently, our investigation provides an observable basis for the policy circles to resolve this unexplored behavioural attribute for credit-constrained online small business owners.

The closest study to our research is Chen et al. (2020), who examine gender-based discrimination using a sample of consumer and business loan applications from China over 2012-2014. They focus on the quality of applicants, and argue that female applicants should have a higher likelihood of funding for they are of better quality (e.g., higher expected profitability) than their male counterparts. Our study complements their findings but prioritizes small business borrowers' likelihood to apply after experiencing one or more earlier turndowns as we consider the gender differences in borrower discouragement. Further, our examination

scrutinizes the data from the perspective of the lenders and the borrowers.[3] Consequently, we differ from Chen et al. (2020) in our contribution to the literature as our focus is the discouragement of small business owners while we elucidate gender-based specificities. Indeed, a large body of research has reached the consensus that female-led businesses face a higher probability of not applying for bank loans than their male counterparties, thus behaving as discouraged borrowers (Ongena and Popov, 2016; Galli et al., 2020).

Our examination extends the literature on gender gap issues in access to finance by considering the potential of internet-based platforms providing rising market opportunities for women business owners. Indeed, the emergence of online peer-to-peer lending platforms has provided businesses owners with a new and powerful tool to improve financial inclusion for female entrepreneurs. For instance, Pope and Sydnor (2011) have argued that the funding gap between female and male entrepreneurs could close due to increasing competition among providers of credit, financial innovations, the emergence of fintech companies, and digitization of financial services. Furthermore, researchers have also started to examine whether digital technologies and internet-based platforms would create new opportunities for women business owners (Orser et al., 2019).

Chinese crowdlending financial intermediaries have several unique properties essential for our empirical investigation compared with traditional commercial bank lending. First, financing through P2P platforms is likely to be more efficient than the conventional route (for instance, bank loans) as the platform directly connects lenders to borrowers in a digital environment. Unlike all online platforms throughout the world, Chinese P2P loan markets are very fast in connecting lenders and borrowers. In China, the average filling time of a loan request is less than a day, whereas in Europe or the USA, it takes several days to fill in a loan application on

[3] In fact, our study shows that female business owners are slightly favoured, on *Renrendai*.com. Yet the effect is not economically significance.

digital platforms (Caglayan et al., 2020b). Second, application costs are very low as borrowers do not need to fill in forms at a bank branch. This feature of online platforms is likely to reduce the number of discouraged borrowers, as borrowers do not need to go through the whole loan application process with a financial adviser. The applicant submits a listing or repeats this process if the application was rejected in the previous round.

To conduct our analysis, we collect data on small business owners' (single or multiple) loan applications from a leading peer-to-peer (P2P) loan platform, *Renrendai.com*, in China.[4] The data span the period from October 2010 to October 2018 and contain information on both loan level and borrower (business) level characteristics in addition to the gender of the business owner as well as the status of each application (failure *versus* success). We start our investigation by estimating the likelihood that a lender would fund a loan given the borrower's socio-demographic characteristics, loan terms, and the number of earlier attempts. In doing so, we check whether investors' funding decisions are gender-biased when lending takes place on a digital platform where no party involved has face-to-face interactions. Our analysis also helps us to see whether persistent applicants are eventually funded. We then turn to borrowers' problem and examine their decisions to apply (or not) after experiencing a failed attempt to raise funds from the platform. This strategy allows us to unveil whether female entrepreneurs are discouraged from applying after a failed attempt. Lastly, to expand our understanding and for robustness purposes, we explore the data by loan purpose and by regional development.

Our empirical exploration yields several important results. We observe that female business owners are more likely to get discouraged compared to their male counterparts after experiencing one or more loan application rejections. In addition, our findings reveal that female discouragement persists at different regional development levels; even in more

[4] See Gao et al. (2020) for an overview of the Renrendai platform.

developed regions, female entrepreneurs are less likely to apply for new funds than male entrepreneurs. Our investigation yields no evidence of discrimination against female business owners on *Renrendai.com*. We find that female applicants have a slight advantage compared to their male counterparts, but this difference is economically insignificant. To our knowledge, our paper is one of the first research to study gender differences in the setting of P2P digital loan platforms, from both the demand and the supply side of the channel. The use of digital technologies may help to offer new opportunities to "destabilize conventional gender differences" (Ughetto et al., 2019). We add to this literature by showing that female business owners are not discriminated against but are more likely to be discouraged from applying for funds after a failed attempt than their male counterparts on the P2P digital loan platform.

The rest of this paper is organized as follows. Section 2 describes the peer-to-peer lending industry in China as well as the *Renrendai.com* platform. Section 3 illustrates the application decision of the small business owners and presents our empirical approach. Section 4 provides our results, subsample analysis, and discusses the findings. Section 5 concludes and provides implications.

2. P2P Loan Data from *Renrendai.com*

Data are hand collected from *Renrendai.com*, one of the largest and fastest-growing P2P platforms in China.[5] The platform was founded in October 2010 and has the largest registered members for P2P lending. As of the end of October 2018, it has facilitated over RMB 73.4 billion (appr. 10.4 billion USD) in loans. *Renrendai* was rated as AAA (the highest level) online lending platform by the Chinese Academy of Social Science and Chinese Fintech Association in 2014 and 2015. Our initial dataset includes about 0.8 million business loan listings posted between October 2010 and October 2018. We include only self-employed and private

[5] See He & Li (2020) for an overview of Chinese peer-to-peer platforms and the legal environment.

businesses in our sample and eliminate the listings that are guaranteed by the platform.[6] As a result, our sample contains 435,990 business loan listings, of which 256,973 listings were funded.

For a business borrower to request a loan, a list specifying the amount of funds demanded must first be created. There is no fee for posting such a list. To set it up, the borrower must upload a written statement to describe the purpose of the loan and provide personal information, including age, education, gender, employment, and marital status. The provision of the national identification card and the disclosure of gender information are compulsory for all applicants on *Renrendai*. Furthermore, the applicant informs income[7] and any ownership of vehicles. Given this information, along with the track record of earlier transactions (e.g., number of rejected, repaid, and repaying loans, default history, or the amount of outstanding credit), the platform provides each applicant a score in relation to the borrower's creditworthiness. Then, a borrower can apply for any amount that can range from 3,000 to 500,000 RMB (appr. from 400 to 70,000 USD).

Once the listing is uploaded, the platform keeps it posted for up to 168 hours. Lenders can browse the listing's page, which covers all the application information provided by the borrowers, and the percentage funded. By assessing both listing and borrower's information, the potential lender can bid on the listing by specifying the amount she wishes to lend out. The minimum bidding amount is 50 RMB (appr. 6.7 USD). If the application is filled, the borrower

[6] In this case, the P2P platform act as a credit intermediary as described in Huang et al. (2021): the platform packages the loan targets and sells them to individual lenders. The platform rather than individual lenders makes the decision on each loan application's success or failure. Our sample keeps only the loan listings posted by the business borrowers on the platform. The platform provides a portal for these individual business borrowers to publicly list their loan demands and individual lenders to view the listings and make the decision to lend or not.

[7] The platform asks each borrower to fill in income by choosing from six categories to encourage a response and simplify borrower's task. The mean value of income for each category is used in our analysis (Bhat, 1994; Gordon-Larsen et al., 2003; Klein et al., 2021). We have experimented with using income variable measured in values (between 1 and 6, where 1 indicates less than 1,000 RMB, 2 means between 1,000 and 5,000 RMB, 3 means between 5,000 and 10,000 RMB, 4 means between 10,000 and 20,000 RMB, 5 means 20,000 RMB to 50,000 RMB, and 6 means more than 50,000 RMB). The obtained results are quantitatively similar and available upon request.

receives the full amount requested from the platform. Otherwise, the committed funds are returned to the investors, and the borrower fails to receive the funding. To construct the data, we track each listing over time and observe whether it is filled or not. Additionally, we extract information on the repayment status of each loan. For each listing, we also download loan characteristics, including the loan amount, interest rate, term, listing time, loan narrative, and borrower characteristics.

Please insert Table 1 about here

Table 1 provides the basic summary statistics of all listings in our data. We observe that the average loan amount is about RMB 78,800 (appr. 11,034 USD) and has a substantial standard deviation implying that there are borrowers who ask for a lot more or a lot less than the average. The average interest rate is in the vicinity of 11.9%. The average term of the loan is 24 months, while the borrowers are allowed to choose any term between 3 months to 3 years with an increment of three months. All loans are uncollateralized and come with a loan narrative that contains on average 97 words. Given the standard deviation on this category (63), it is clearly the case that some borrowers are very parsimonious in expressing their intentions for the use of funds while others could be much more verbal. Narratives for each loan request explain why the loan is needed and why creditors should believe that the borrower is trustworthy and will pay back the capital and interests. The table also shows that the average approval rate of all business listings on the platform is 59%. However, when an applicant experiences a rejection on his (her) first application, the approval rate for the next application drops to about 2.2%. The approval rate of a loan application falls to 1.3% and 1.2%, respectively, on each subsequent attempt if the borrower has two and three failed earlier funding requests.

The descriptive statistics on borrowers' characteristics are presented in Panel B of Table 1. 25% of the applicants have a university degree; 63% of them are married, and 26.7% are female. The average applicant is about 33 years old and has a monthly income of RMB 4,744

(appr. 660 USD). About 14.5% of the applicants have a vehicle, and they have on average less than two years of work experience. Table 1 also shows that after an initial rejection of a loan application, 29.4% of borrowers will submit another loan application. Overall, the descriptive statistics are similar to earlier studies that have used data from *Renrendai.com* (e.g., Caglayan et al., 2020a).

In Table 2, we report the loan and borrower characteristics of female and male business applicants. As shown, 26.7% of the borrowers in our data are comprised of female business owners. We observe that female businesses owners, on average, request a larger loan amount in comparison to males. Female applicants propose to pay on average 0.98 percentage points lower than males, a difference statistically significant at the 1% level, while they request loans for a longer-term than male borrowers. Females also appear to submit a more diligent narrative[8] and have a much higher success rate (78% for females vs. 52% for males) of their loan applications. The descriptive statistics on listing characteristics do not suggest any obvious evidence of gender-based discrimination in the peer-to-peer loan market.

Please insert Table 2 about here

When we examine borrower characteristics, several differences between female and male business owners stand out. We find that female business owners are more educated, slightly older, and have longer work experience than their male counterparts. Female applicants have higher incomes, and they are less likely to have a car. The average credit score of a female applicant is 143, while male borrowers, on average, have a lower credit score of 102. Although these statistics place female business owners at a better standing than males for credit applications, to our surprise, we find that female business borrowers are less likely to apply for

[8] The average number of words used in loan listing narratives posted by female business borrowers is more than that of male borrowers.

a new loan after an initial rejection. The differences between the variables for male and female applicants that we report in Table 2 are statistically highly significant.

2.1 To apply or not to apply

Research has heavily depended on surveys to examine credit-constrained business owners and borrower discouragement. Mac an Bhaird et al. (2016) report that discouraged business owners manage small, younger firms with a low turnover and high debt to assets ratio. Han et al. (2009) suggest that riskier borrowers have higher probabilities of discouragement. They also find that firm and firm-owner characteristics such as firm size and personal wealth affect discouragement. Cole and Sokolyk (2016) document that discouraged firms are significantly different from denied firms on several dimensions, including firm size, profitability, owner age, and the number of sources of financial services. Based on a postal survey, Freel et al. (2012) investigate UK small and medium-sized enterprises (SMEs) who are in need of bank debt and present evidence of borrower discouragement. Pindado et al. (2006) argue that small business borrowers are discouraged from applying for a loan, and consequently, they must resolve their funding problems through means other than the traditional financing routes.

A few empirical studies examined the correlation between gender and loan applications. Verheul et al. (2012) provide evidence for gender differences in risk tolerance for small business owners. Women business owners are deemed to have a greater propensity for risk aversion in terms of financial behaviours across various activities, including business funding (e.g., Barber and Odean, 2001). Li et al. (2020) examine gender differences in self-risk evaluation on the P2P lending market and find that male borrowers are more likely to seek benefits by offering lower interest rate premiums than female borrowers. Cowling et al. (2019) find that gender and risk tolerance were the dominant factors in explaining female entrepreneurs' lower demand for bank loans by examining SME Finance Monitor survey data. Women business owners, due to discouragement, use lower amounts of funds for their

businesses than their true needs, affecting venture sustainability and growth (Carter et al., 2007).

In contrast to the literature, we base our investigation on actual small business loan application data from a prominent peer-to-peer lending platform in China. We define a small business borrower as discouraged if we do not observe a new application from the same applicant after the applicant experiences one or more loan rejections.[9] Although one can argue that potential borrowers stop applying because they do not need funding anymore, this does not seem to apply to our data. The average time between the initial rejection and a new loan application is about 78 days. The time interval between applications reduces to 60 days, and further to 52 days when the applicant experienced two or three earlier rejections. Hence, it seems unlikely that the need for funding would disappear quickly.[10]

Please insert Figure 1 about here

Figure 1 displays the decision tree of all possibilities that the applicants at *Renrendai.com* have followed in our sample. The figure provides the number of applications at each Stage i (i = 1,..., 4), who applied for funds, the number of declined applications ($Rejected_i$ with i = 1,..., 4), the number of filled listings ($Approved_i$ with i = 1,..., 4) and the number of applicants who withdrew from the platform ($Discouraged_i$ with i = 1,..., 3) upon failing to raise funds from an earlier application.[11] Stage 1 displays the total number of first-time business loan applicants. Initially, there are 360,126 lists posted by business owners to be considered by the lenders for funding. Out of these first-time applications, 248,404 are funded, and 111,722 (grey box) did

[9] Caglayan et al. (2020b) define discouraged borrower as an individual who does not submit a new loan application after having experienced one or more loan request rejections.
[10] There is always a possibility that an alternative source of funding (e.g. another platform or informal lending) is found. Unfortunately, this information is not observable.
[11] We do not claim that only the high-quality borrowers drop out of the market. It is also expected that some of the risky borrowers will self-select and leave the market because of expected loan denial. The loss of better-quality applicants upon a rejection can lead to the collapse of the market, as at the limit the only borrower type left for funds would be those with a high-risk profile.

not receive funding, Rejected$_1$. Those who did not get funding, applicants in Rejected$_1$ box, are then split into two groups; some of them decided to apply a second time after the initial rejection (Stage 2[12]), and the rest dropped out. Those who dropped out after the first rejection are identified as discouraged borrowers (Discouraged$_1$). Looking at the figure, we see that 32,875 individuals, rejected in the first round, have applied for funds again (Stage 2), while 78,847 of the applicants were discouraged. The figure displays all possibilities up to 4 unsuccessful loan applications. We stop our scrutiny at Stage 4 as the data become sparse.

3. Empirical Strategy

In what follows, we discuss our empirical approach to examine both lenders' and borrowers' behaviour. We propose and estimate several logit models to evaluate the factors that affect lenders valuation and those that borrowers consider in submitting a new application (or not) after experiencing a failed funding request. All models scrutinize the role of gender.

3.1 Lender behaviour

Are female business owners discriminated against in online P2P markets? Do lenders extend loans to persistent applicants? Which loan and individual characteristics play a positive role in being funded? These are the main questions we address in this section.

Iyer et al. (2015), using data from a prominent US peer-to-peer platform (prosper.com), examine the efficiency of screening in peer-to-peer markets and find that individual lenders depend mainly on hard financial criteria, as well as non-standard information when making their funding decisions. In our models, we also scrutinize to what extent and which of the loan-specific and applicant-specific factors affect the funding decision of lenders on *Renrendai.com*. In our investigation, we also examine whether lenders extend loans to persistent applicants.

[12] Borrowers are allowed to submit identical loan application after initial rejection(s) on the platform. However, our data shows only 3.6% of resubmitted loan listings are the same as earlier application(s) made by the borrower.

Our empirical models pay particular attention to the gender of the applicant to understand whether lenders' funding approvals are gender-biased.

Our first logistic model takes the following form:

$$\text{Prob}(Funded_j = 1) = \Lambda(\alpha + \psi\, Female_j + Loan_j\beta + Borrower_j\gamma + Z_j\zeta) \quad (1)$$

where *j* denotes the borrower. The dependent variable, *Funded*, is set to 1 if the loan is approved and zero otherwise. Λ denotes the logistic distribution function. Gender may be an important determinant in raising external funds, and its role is widely discussed in academic and policy circles to examine its pertinence on discrimination in gaining bank loans (Marlow and Patton, 2005; Alsos et al., 2006). To answer whether female business owners are discriminated against compared to male business owners, we include in equation (1) the Female dummy, which equals one if the business loan applicant is female; and zero otherwise. If investors discriminate against applicants by gender, then the coefficient should be significant.[13]

The vector *Loan* includes the rate of interest that the borrower is willing to pay, the requested loan amount, loan term, the word count of the loan narrative. The vector *Borrower* contains variables that capture the borrower's personal characteristics, including university education, income, years of work experience, vehicle ownership, marriage status, age, and the credit score assigned by the platform. The last term, *Z*, captures the applicant's previous experience with the platform as it provides the cumulative number of earlier failed loan applications. Hence, we can address whether the persistent applicant is rewarded a loan.

Using this model, we expect to observe that lenders will fund those applications for which the probability that the loan will be fully paid is high. This aspect is captured by two variables included in the vector *Loan*: credit rating and the interest rate charged. We expect credit rating

[13] It will be negative if females are discriminated against males and *vice versa*.

will have a positive effect on funding probability, and interest rate should have a negative effect. Higher interest rates indicate an increase in the riskiness of the borrower; consequently, the lower the interest rate, the less risky the borrower is. Along the same lines, investors are likely to fund smaller loans as listings that demand smaller amounts generally need fewer lenders to fulfil the loan request, which increases the probability of funding success (Herzenstein et al., 2008). Furthermore, investors may consider the amount borrowed as a risk factor and avoid lending out a large amount of money to the same person to control risk (Cai et al., 2016). Therefore, listings that demand a larger sum may have a lower funding approval rate.

Concerning the role of borrower characteristics on lenders, we have the following expectations. Borrowers with less education are expected to have lower financial literacy, and the cost of borrowing might not be their priority (Lusardi and Mitchelli, 2007). If so, such an applicant is more likely to be rejected for potential lenders would use education as an indicator to gauge borrowers' capability to repay the loan. However, there are many business owners who did not go through a rigorous university degree programme but have a keen sense of business acumen. In that sense, education may not be relevant at all from the perspective of lenders. In contrast, we expect income to have a positive effect on getting funded. Borrowers with lower income are more likely to be rejected because the personal wealth of borrowers would be taken as collateral.

Prior employment experience is an important factor in debt financing (Colombo and Grilli, 2007). Hence, we expect that the longer the applicant's work experience, the higher the probability that the listing will be funded. Yet, characteristics such as ownership of a car or being in a marriage should not have a significant role in receiving funding from the investor. Given that the investigation focuses on small business owners, lenders may not see owning a car as fundamental to running their business. It is perhaps better to use funds to develop the

business rather than buying a new car, as car ownership comes with additional costs. Likewise, marriage, although it may be used as a signal for stability (and if so, the effect should be positive), is not expected to directly impact loan success. Younger individuals tend to be optimistic and ambitious about their businesses (Parker, 2004). However, with age, an individual acquires experience and human capital. Several studies have documented that willingness to take risks decreases as borrowers age (e.g., Dohmen et al., 2017). Hence, we expect lenders to fund mature borrowers, and that age would take a positive coefficient. To capture the potential impact of non-linearities associated with age, we add a quadratic term.

The model, different from any earlier work, addresses the question of whether a persistent applicant is funded at some point in the future. To capture that, we include a variable which records the previous failed applications of the applicant. A positive coefficient suggests that persistence pays off.

3.2 Borrower behaviour

To examine the attributes that affect borrowers' likelihood of seeking funds from the platform after experiencing one or more failed earlier funding requests, we use a separate logistic model that looks at the data from the perspective of the applicant. The model incorporates the *Female* dummy variable to highlight whether female-business-owners are discouraged from reapplying after experiencing a failed attempt. Our model also contains several additional variables that capture listing and borrower-specific characteristics. In estimating the model, we first limit our sample to those who were declined in their first loan application. We then explore the question of discouragement for female/male business owners by estimating the following model up to 3 unsuccessful attempts (for each node in Figure 1):

$$\text{Prob}(Applied_i = 1) = \Lambda(\alpha + \psi\, Female_j + Loan_i\beta + Borrower\gamma) \qquad (2)$$

where *i* denotes the borrower.[14] The dependent variable, *Applied,* is set to 1 if the borrower has applied for a loan and zero otherwise. Λ denotes the logistic distribution function. *Female* equals one if the applicant is female and zero otherwise. *Loan* and *Borrower* are vectors that capture several loan and borrower characteristics. The vector *Loan* contains the information on loan requests posted by borrowers, including the loan amount, requested term, the rate of interest that the borrower is willing to pay, the word count of the loan narrative. The vector *Borrower* contains variables that capture borrower characteristics, including education, graduate university, income, years of work experience, marriage status, age, and a dummy whether the borrower has a car and the credit score assigned by the platform. Because we estimate equation (2) for three different samples of applicants, starting with single loan rejection and going up to three loan rejections, our parameter estimates would reflect the impact of previous failed attempts on the role of loan and listing characteristics.

The characteristic that we are most interested in is the gender of the business-owner applicant. Existing studies have shown that female borrowers are less likely to apply for a loan due to lack of self-confidence, perception of supply-side discrimination, and lower propensity for risk.[15] For instance, Sonfield and Lussier (2004) specifically argue that women are usually more prudent, less confident, less aggressive, and have inferior leadership and less problem-solving abilities when making decisions under risk. Risk aversion influences demand for loans, and women business owners show greater reluctance to seek funding (Croson and Gneezy, 2009; Huang and Kisgen, 2013). A cornerstone in these arguments is that women business owners anticipate the negative outcomes, which typically trigger a discouragement mechanism (Ughetto et al., 2019). Female business owners happen to be discouraged from applying for funding due to their fear of rejection or (mistaken) perception of being less creditworthy,

[14] See Chakravarty and Xiang, 2013 or Cole and Sokolyk, 2016 for a similar modelling strategy.
[15] See for instance Marlow and Patton, (2005) and Alsos et al. (2006) among others.

resulting in foregone future business growth opportunities (Mijid, 2015). Suppose female applicants on Renrendai.com embody similar characteristics. In that case, we expect them to leave the platform quicker than their male counterparts when the previous application is unfilled, as female applicants would think lenders will not provide them with funds should they resubmit a loan application.

In relation to the other variables, we expect to find a positive role for credit score and interest rate. The higher the credit score a borrower has, the higher the credit limit is assigned to the borrower. Hence, the borrower with a higher score is expected to apply despite an earlier failure. We also expect that the business owner, who needs funds, would offer to pay a higher interest rate to raise some funds to run her business. Thus, those borrowers who contemplate having a relatively lower credit score and who are not willing to pay higher interest rates are likely to be discouraged and exit the platform early on. Income is an important determinant: borrowers with higher income may be in less financial neediness and greater confidence of lower rejection rates; therefore, they are more likely to apply for credit (Freel et al., 2012). In contrast, applicants with lower income levels may lack confidence in their self-assessment (Kon and Storey, 2003), for lenders use the income to signal their ability to repay. Furthermore, borrowers' income could indicate creditworthiness and is expected to have a positive role in repeat applications.

Education can be taken as a signal for applicant awareness and quality. Borrowers with less education can be considered to have lower financial literacy, while better-educated applicants can evaluate the time value of money, and they would be unwilling to pay high interest rates. Hence, educated borrowers would drop from the market earlier after experiencing a failed attempt for they would not want to experience another funding application refusal. If so, education should have a negative coefficient. The loan term is expected to have a positive role. Given SMEs borrow funds to finance their business activities, we would expect that the demand

will be for longer-term loans. However, it is unclear if SMEs would prefer a larger or a smaller loan.

Other individual characteristics such as the length of work experience with the same employer and ownership of a vehicle are expected to have a positive effect on applications. Individuals with a track record for employment are expected to succeed in their loan application, and these applicants are expected less likely to be discouraged (Mac an Bhaird et al., 2016). Colombo and Grilli (2007) argue that prior employment has a positive effect on debt financing. Likewise, an applicant may consider ownership of an asset, such as a car, which may help overcome the presence of asymmetric information problems, as these assets can be considered as collateral by the lenders. When we consider age, we can argue that younger borrowers tend to be over-optimistic and more ambitious. However, with age an individual gains experience and human capital. The model contains both the level and squared age to control for such nonlinearities. Finally, we do not have a firm expectation of whether being in a marriage would have a positive or a negative effect on application, and we allow the data to determine its impact.

4. Results and Discussion

This section presents our empirical results starting with lender behaviour in screening credit constrained small businesses. We then focus on borrower behaviour and investigate what factors trigger discouragement. Finally, we examine whether the loan purpose or the development level of the region where the applicant runs the business impacts both lender and borrower behaviours.

4.1 Lender decision to fund an application

Table 3 reports the marginal effects of small business characteristics on funding approval. The first column presents results with borrower characteristics only, the second column adds loan

characteristics, and the last column adds a variable that captures the number of failed funding requests of the applicants. The first row of the table highlights the role of gender.

Inspecting the table, we see that *Female* dummy takes a statistically highly significant and positive coefficient. However, its economic significance is low. Thus we are inclined to argue that lenders consider female and male business owners similarly. This finding is in line with some of the earlier research that has examined the link between gender and debt financing. For instance, Eddleston et al. (2016) report no evidence of gender discrimination in the access to loans. Studies on peer-to-peer lending in the United States (Pope and Sydnor, 2011; Duarte et al., 2012) and China (Chen et al., 2017) find that women have better chances of obtaining funds than males.

The observation that female business owners can borrow without any discrimination, while perhaps slightly favoured, on *Renrendai*.com is important on its own. A possible explanation for this observation is that female small business entrepreneurs entering the P2P market are more educated, have higher income, and higher credit scores than their counterparties, as shown in Table 2. The evidence also suggests that lenders on *Renrendai.com* are rational in placing their hard-earned cash, and they do not pay attention to the gender of the applicant as a hindrance to funding. In the light of our findings, it is most important that the platform operators and the policymakers should strive to encourage female business owners to apply for funds using online platforms for as long as their business plans are sound.

Table 3 also shows that several borrower-specific and loan-specific characteristics affect lenders' funding decision problems. We find that the interest rate has a negative and a highly significant coefficient. The credit score, likewise, is highly significant and has a positive coefficient as expected. Creditors (investors) seek to finance high-quality, low-risk entrepreneurs. This can be achieved by funding those applicants with good credit ratings so that the overall cost of borrowing would be lowered. Approved loans are more likely to be

smaller and run a longer-term. These observations are meaningful. Rather than financing larger projects, investors would prefer to finance several smaller projects to diversify their portfolio. But while doing this, the loan could have a longer-term providing the investor with a set stream of income for a longer time. We also find that narratives, soft information, have a positive role. This suggests that lenders appreciate detailed explanations about the intentions of the borrower. Hence, funding applications with shorter narratives, which are far from explaining what will be achieved with the funds, would not convince the lenders to extend a loan to the applicant. In that sense, small business borrowers who pay attention to explaining their business needs and plans are more likely to have their listings filled.

Please insert Table 3 about here

Employment length has a positive effect on investors' decision-making process. Borrowers without a long enough employment record may be considered risky because employment history provides information to assess borrower performance and borrower ability to pay back the loan (Reuber and Fischer, 2005). We also find that income of the borrower has a positive effect on the decision to invest. Given that investors would like to fund low-risk borrowers, both employment length and income level provide valuable information about the performance of business owners. Further observing the table, we find that ownership of a vehicle has a negative sign. Perhaps, vehicle ownership is seen as a source of ongoing expense but not as collateral. Being in a marriage does not impact the lending decisions of investors. Education is statistically insignificant in all specifications. This suggests that lenders do not necessarily fund entrepreneurs who have better education but those with good business plans as detailed in their loan narratives. Age and age squared take positive and negative coefficients, respectively: borrowers receive more funds as they get older, while this effect declines over time. We find that the number of previous failed applications has a negative effect on lenders' funding

decisions. This finding suggests that lenders use earlier failed funding application records to assess the quality of applicants returning to the platform.

4.2 Borrower decision to apply or not

Columns (1)-(3) of Table 4 present the results for equation (2), which examines a borrower's decision to apply while she is allowed up to three rejected funding applications. Table 4 shows that the coefficient associated with the gender of the applicant is highly significant and negative. Female entrepreneurs are 1-2 percentage points less likely to apply again compared to their male counterparts if they have an earlier failed attempt to raise funds from the platform. This suggests that female business owners drop out of the market quicker than their male peers after experiencing failed funding request, or they feel a new application will not go through, either. In this context, Freel et al. (2012) argue, based on UK small business survey data, that female business owners simply do not approach banks for loans because of fear of rejection. Along these lines, Marlow and Patton (2005) and Fairlie and Robb, (2009) argue that the discrepancies in funding between male and female-owned businesses may be due to women entrepreneurs' reluctance to seek finance. Chaudhuri et al. (2018) and Galli et al. (2020) indicate that women entrepreneurs tend to be more risk-averse and less confident than men, which causes them to be more skeptical about their ability to successfully obtain loans. Consequently, women entrepreneurs can be discouraged from pursuing external finance due to their misperceptions of the possibility of rejection.

Please insert Table 4 about here

When we examine the remaining loan characteristics, we gather the following observations. Interest rate plays an important role in borrowers' decision to reapply. The coefficient associated with the interest rate is positive and significant at the 1% level in columns (2) and (3). Small business owners who come back to the platform after experiencing earlier rejections

are willing to pay higher interest rates to get funded.[16] That is, a business owner who is not prepared to pay high-interest rates will be discouraged to return to the platform. This finding supports Brown et al. (2011), who showed that high interest rates are the most significant factor that affects creditworthy borrowers' decision not to apply for loans. Yet, when we consider the lenders' funding decision problem along with the borrowers' decision to apply, small business borrowers with higher interest rates are less likely to receive funding as lenders care about applicants with business acumen. Hence, some of the discouraged business owners could receive funding for as long as their business plans are creditworthy. The loan term has a significant and positive effect for the first round suggesting that businesses seek long-term credit. However, borrowers that return to the platform after experiencing a failed attempt try to obtain loans with a shorter term. This behaviour, in a sense, highlights the severity of the credit constraints; when a business cannot raise funds to be paid over a longer-term, the attention turns to raising funds for a shorter period, even at the cost of paying higher interest rates. Word count and loan narrative do not seem to play a significant role when business owners submit a new loan application following earlier failed attempts.

When we turn to the borrower characteristics, we see that credit score assumes a positive and significant coefficient at the 1% level in all columns. That is, those with better credit ratings apply again despite being rejected in a previous round. Hence, we can say that small business owners with low credit scores drop out of the platform early on. Our empirical analysis also shows that better educated small business owners are discouraged after experiencing two or three funding application rejections. The coefficients associated with education are negative and significant in columns (2) and (3). Better educated small business owners are expected to be financially literate and can evaluate the return from their project given the interest rate they

[16] Small business owners who re-apply for funds on average pay a higher interest rate by 7.1%, 5.8%, and 8.1% after a single, two and three failed attempts, respectively.

have to pay to attract a lender. Hence, having calculated the amount they have to pay back to the lenders at higher interest rates, they may think it is not worthwhile to seek funding through the platform after a failed application. Being educated also helps the business owners to forecast the business potential better, and this knowledge may trigger an option to wait.

Income has a positive and significant effect on submitting the initial loan application. However, income exerts no significant impact when the business owner submits loan applications after experiencing two or more failed attempts. That is, borrowers with low income are not discouraged from applying for a loan after experiencing a loan rejection in the platform, even if they have low repayment ability. This observation suggests the severity of credit constraints within the small business community. Vehicle ownership also increases the likelihood of applying after a failed loan request. However, some attributes such as marriage or the length of employment do not play a consistent role, although they could be taken to measure stability or creditworthiness.

4.3 Subsamples

So far, we have examined the data from the perspective of lenders and borrowers. This investigation has led to several interesting and new findings. In particular, we show that lenders seem to fund female business owners' funding applications more than their male counterparts' applications, while female borrowers tease themselves out from the platform after experiencing a failed funding application earlier than their male counterparts. In this section, we examine whether our findings in Table 3 receive support when we allow the purpose of loan demand to vary between working capital expenditures *versus* fixed investment expenditures. We then investigate whether results are driven by the fact that the applicant is from a more (less) developed part of the country.[17] To capture the state of regional development, we use tier 1 city

[17] Small business borrowers are required to provide the location of their businesses to the platform.

classification.[18] It is important to examine the sample after splitting the data based on regions because there are significant variations of development across China. Differences across regions affect financial constraints faced by SMEs, as well as their cost of borrowing and the availability of information.

The results for specific loan purposes are presented in columns (1) and (2) of Panel A of Table 5. In columns (3) and (4) of the panel, we present evidence for lending behaviour between developed *versus* less developed regions. Panel B presents whether loan usage and business location affect borrowers' decision to apply. Note that we only report that the coefficients associated with the Female dummy for the effects of the control variables were similar to those reported in the earlier tables.[19]

Please insert Table 5 about here

Panel A shows that lenders marginally prefer to approve female funding applications over males. Females seem to do better than males, especially when they apply from low developed regions. However, this result, as we observed in Table 3, is not economically meaningful.

Panel B examines borrowers' decision to apply. Overall results are similar to those presented in Table 4. Females' tendency to apply after an earlier failed funding request is less than their male counterparts. In particular, the difference is significant when females are seeking loans to use for their working capital. Female entrepreneurs are two percentage points less likely to seek funds for their working capital expenditures than their male counterparts if they have an earlier failed attempt to raise funds. However, the data provide no evidence of any significant difference between male and female business owners when entrepreneurs seek loans for fixed

[18] China's cities are typically divided into four categories, based on economic development; Tier 1 cities include most developed metropolitan areas (Glaeser, et al., 2017): Beijing, Shanghai, Guangzhou, Shenzhen, Chengdu, Hangzhou, Chongqing, Wuhan, Suzhou, Xi'an, Tianjin, Nanjing, Zhengzhou, Changsha, Shenyang, Qingdao, Ningbo, Dongguan and Wuxi.

[19] Full tables are available upon request. To conserve space, we focus on estimates for the *Female* dummy only.

investment expenditures. When we examine the impact of regional development on female applications, we see that female entrepreneurs do not appear to behave differently on their application pattern across regions with different levels of development. Columns (3) and (4) of the panel show that female entrepreneurs are less likely to come back to the platform to submit a new loan application compared with male entrepreneurs after a failed attempt.[20] Our analysis provides further evidence on female discouragement: female entrepreneurs from developed and less developed regions are about two percentage points less likely to seek funds than their male counterparts if they have an earlier failed attempt to raise funds.

4.4 Propensity score matching estimation

Our findings show that lenders do not discriminate against female business owners on gender, while female borrowers withdraw themselves from the platform early.[21] We recognize the potential problem of unobservable variables and its solution using instrumental variable (IV) estimation. However, the instrument exclusion restriction that underlies the validity of instruments is often suspect; that is, instruments are only plausibly exogenous (Conley et al., 2012). Even if instruments satisfy the exogeneity assumption, they may be weak instruments (Bound et al. 1995). Chen et al. (2020) used the gender ratio of residence city of the borrower as an instrument to account for the probability of the borrower being female. However, the instrument validity of their model cannot be verified because it is exactly identified. IV estimation results show no measurable gender effect on loan application success.

Another possible concern is the possible differences in borrower and listing characteristics between female and male applicants. These differences may lead to the observed funding

[20] This finding resonates with Galli et al. (2020) who showed that female discouragement persists in different phases of the business cycle even when business environment is favourable to the success of enterprises.
[21] A possible explanation is that female business borrowers who had an earlier rejection may have worse credit quality than male counterparties. We compare the default rates of female and male business borrowers after an initial rejection and observe that the default rates of female and male business borrowers are statistically the same.

decisions of lenders and the subsequent borrower discouragement problems. We address this concern by one-to-one matching male and female applicants referring to their borrower and loan term characteristics and estimate average treatment effects on the treated (ATT).[22] This approach is applied for modelling i) borrowers' decisions to apply or not and ii) lenders' funding decisions. Columns (1) – (3) of Table 6 presents the average treatment effects of dummy *Female* on borrowers' decision to apply or not. Dummy *Female* takes a negative and significant coefficient in the first two columns, supporting our previous results. The probability of female borrowers re-applying for funds will be 1.2% and 2.2% less than their male counterparties after a single and two failed attempts, respectively. These findings from the matched data provide consistent and firm evidence that female-owned businesses are more likely to refrain from applying for credit than their male counterparties. Column (4) of Table 6 presents the average treatment effects of dummy *Female* on whether lenders approve (or do not approve) a loan. It shows that dummy *Female* is positive yet economically insignificant. The propensity score matching results are consistent with our earlier findings that female small business borrowers tease themselves out of the market after a failed attempt earlier than do their male counterparts and that they are not disadvantaged on the platform with regards to the probability of loan request approval.

A recent study by Chen et al. (2020) examines the gender gap of borrowing success at *Renrendai.com* using both consumption and business loan applications in a shorter sample period. We, therefore, restrict our sample to match theirs and estimate the model for the period 2012 – 2014. Results reported in Column (5) provide comparable results, suggesting that female borrowers' loan success rates are not significantly different from those of male borrowers. Column (6) extends the time span from 2012 to 2018. In this case, we observe a

[22] We have also tried nearest neighbour matching and received quantitatively similar results (full results are available upon request).

significant and positive coefficient of dummy Female, which is consistent with our earlier findings. As we discussed earlier, the effect is economically insignificant. When female business borrowers apply for credit, they do not seem to face gender discrimination from the lenders at the P2P platform.

Please insert Table 6 about here

5. Conclusion

In this paper, we examine whether female small business owners are disadvantaged in raising funds from a prominent P2P platform in China or select themselves out from the platform when an earlier application is not filled by the investors (lenders) on the platform. We find no evidence of discrimination against female business owners on *Renrendai.com*, one of China's largest digital loan platforms. Female business owners have a slight advantage compared to their male counterparts, but this difference is not economically significant. Furthermore, constructing subsamples by loan purpose and regional development, we, once more, show that females do well in raising funds from the platform. This is perhaps because female business owners are much more diligent in providing and communicating their business plans. Our data reveal that lenders are mainly concerned about providing funds to low-risk borrowers who would pay back the interest and the capital on time, without much concern about the gender of the borrower. These findings support the idea that digitalized loan markers are fairer.

To our knowledge, we provide the first evidence and offer a step forward in furthering our understanding of discouraged business borrowers in a digitalized lending market. An important observation we unveil from the data is that female applicants are more easily discouraged after an earlier failed funding request. Indeed, compared to their male counterparts, female entrepreneurs are 1 to 2 percentage points less likely to return to the platform after experiencing an earlier failed funding application. Our investigation further shows that small business

applicants who submit a new listing after a failed application are willing to borrow at higher interest rates. As one would expect, the probability of discouragement declines as applicants' credit scores improve.

Given our findings that lenders on *Renrendai.com* do not discriminate female SME owners, but female entrepreneurs select themselves out from seeking funds earlier than their male counterparts, we argue that it would be important for online lending platforms to stress that female small-business owners can succeed in their loan applications for as long as they have sound business plans. Without such an initiative, females will continue to single themselves out of the market. We also suggest that it would be useful for regulatory bodies and P2P lending platforms to develop training and online assistance to encourage small business owners but more so female entrepreneurs. Furthermore, given the positive aspects of digital financing, both policymakers and fintech companies should communicate with the stakeholders about the benefits of financial innovations. The results from this study could be of use to policymakers for developing a better environment in other developed or emerging economies. We suggest further investigation along these lines using data from other countries.

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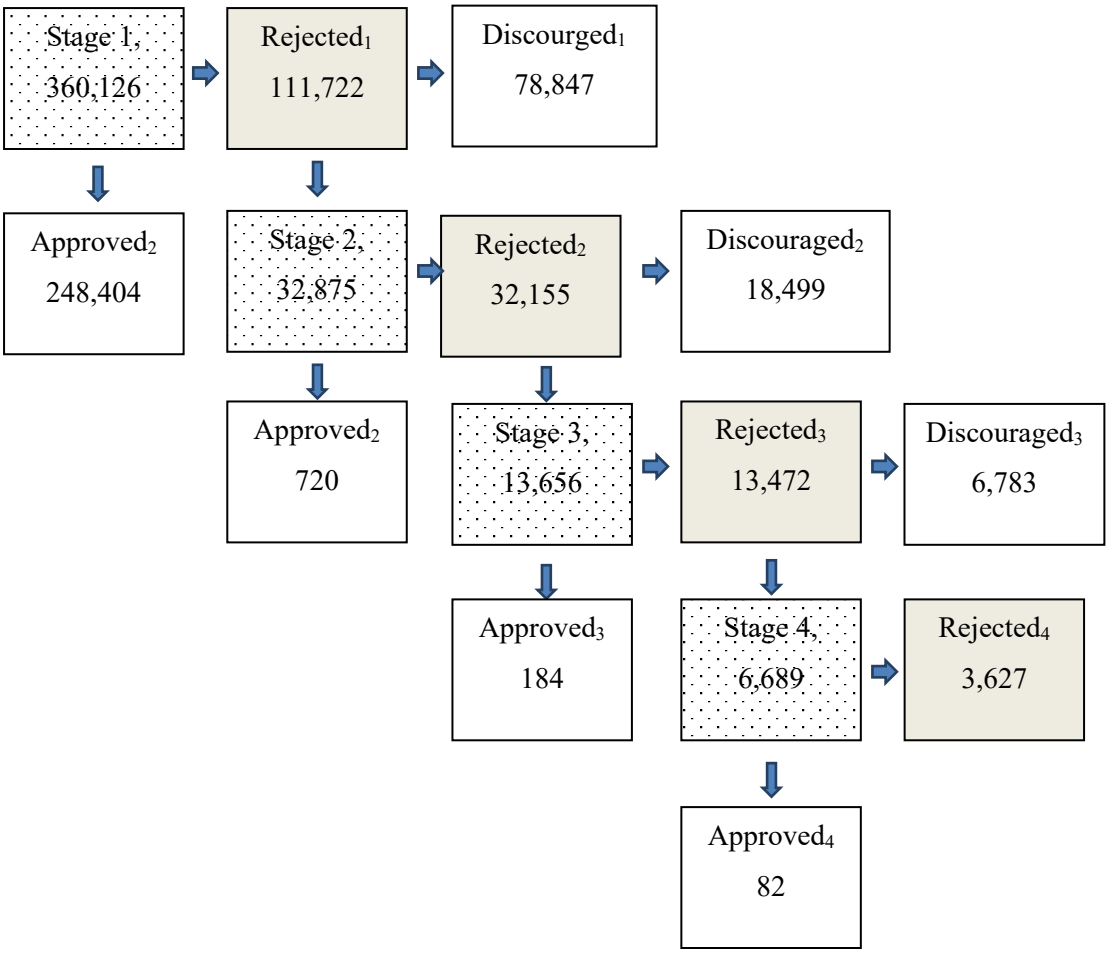
Figure 1. Dichotomy of decision making by small business borrowers and lender.



Note. This decision tree shows the number of loan requests (dotted box) along with rejected (shaded box) and funded (Approved) applications. Those who dropped out of the platform (Discouraged) are also shown. The number of observations in each stage is reported.

Table 1. Descriptive statistics: All business listings.

Variable	Mean	SD	Median	P25	P75
Panel A: Listing details					
Loan Amnt (RMB 000)	78.811	85.311	55.8	30	100
Int. Rate (percent)	11.927	2.712	11	10.2	13
Term (months)	24.119	12.062	24	12	36
Word count	96.560	62.917	95	49	113
Funded	0.589	0.492	1	0	1
Panel B: Borrower characteristics					
Age	33.384	7.802	32	27	38
Education	0.250	0.433	0	0	1
EmpLength	1.511	1.209	1	1	2
Female	0.267	0.442	0	0	1
Income (RMB 000)	4.744	1.303	5	4	6
Marriage status	0.631	0.483	1	0	1
Vehicle	0.145	0.352	0	0	0
Credit score	112.868	79.344	180	20	180
Applied	0.294	0.456	0	0	1

Note: Number of observations: 435,990. *Loan Amnt* is the amount of loan requested by the borrower in thousand RMB. *Int. Rate* is the rate of interest in percentages (%) that borrower is willing to pay. *Term* is loan maturity in months. *Word count* is the word count of loan narrative posted by the borrower. *Funded* is a dummy variable, equal to 1 if the listing is funded; 0 otherwise. *Age* is the age of borrower in years. *Education* equals to 1 if the borrower has at least a university degree. *EmpLength* is work experience in number of years (four categories are available for the borrower to choose from: less than 1 year, between 1 and 3 years, between 3 and 5 years, and more than 5 years. The mean value for each category is used). *Female* equals to 1 if the borrower is female; 0 otherwise. *Income* is the monthly income of the borrower in thousand RMB (six categories are available for the borrower to choose from: less than 1000, between 1000 and 5000, between 5000 and 10000, between 10000 and 20000, between 20000 RMB to 50000, and more than 50,000. The mean value for each category is used). *Marriage status* equals to 1 if the borrower is married; 0 otherwise. *Vehicle* equals to 1 if the borrower has a car; 0 otherwise. *Credit score* is the credit score of the borrower (as of when the listing was created). *Applied* equals to 1 if the borrower summited a loan application after first rejection; 0 otherwise.

Table 2. Descriptive statistics: Female *versus* male borrowers.

	Female borrowers			Male borrowers			Mean diff.	p-value of diff. (t-test)
Variable	Mean	SD	Median	Mean	SD	Median		
Panel A: Listing details								
Loan Amnt (RMB 000)	86.79	73.00	76	75.91	89.19	50	10.88	0.000
Int. Rate (percent)	11.21	2.16	10.2	12.19	2.84	12	-0.98	0.000
Term (months)	28.81	10.60	36	22.41	12.11	24	6.4	0.000
Word count	108.87	55.12	98	92.08	64.95	92	16.79	0.000
Funded	0.78	0.42	1	0.52	0.50	1	0.26	0.000
Panel B: Borrower characteristics								
Age	34.28	7.75	33	33.06	7.79	31	1.22	0.000
Education	0.27	0.44	0	0.24	0.43	0	0.03	0.000
EmpLength	1.68	1.27	2	1.45	1.18	1	0.23	0.000
Income (RMB 000)	4.82	1.29	5	4.71	1.31	5	0.11	0.000
Marriage status	0.65	0.48	1	0.62	0.48	1	0.03	0.000
Vehicle	0.07	0.25	0	0.17	0.38	0	-0.1	0.000
Credit score	143.31	67.59	180	101.80	80.40	148	41.51	0.000
Applied	0.28	0.45	0	0.30	0.46	0	-0.02	0.000
N	116,250			319,740				

Note: This table reports loan and borrower characteristics of female and male business borrowers. *Loan Amnt* is the amount of loan requested by the borrower in thousand RMB. *Int. Rate* is the rate of interest in percentages (%) that borrower is willing to pay. *Term* is loan maturity in months. *Word count* is the word count of loan narrative posted by the borrower. *Funded* is a dummy variable, equal to 1 if the listing is funded; 0 otherwise. *Age* is the age of borrower in years. *Education* equals to 1 if the borrower has at least a university degree. *EmpLength* is work experience in number of years (four categories are available for the borrower to choose from: less than 1 year, between 1 and 3 years, between 3 and 5 years, and more than 5 years. The mean value for each category is used). *Female* equals to 1 if the borrower is female; 0 otherwise. *Income* is the monthly income of the borrower in thousand RMB (six categories are available for the borrower to choose from: less than 1000, between 1000 and 5000, between 5000 and 10000, between 10000 and 20000, between 20000 RMB to 50000, and more than 50,000. The mean value for each category is used). *Marriage status* equals to 1 if the borrower is married; 0 otherwise. *Vehicle* equals to 1 if the borrower has a car; 0 otherwise. *Credit score* is the credit score of the borrower (as of when the listing was created). *Applied* equals to 1 if the borrower summited a loan application after an initial rejection; 0 otherwise.

Table 3. Lender decision to approve a loan or not.

	(1)	(2)	(3)
Female	0.002***	0.003***	0.002***
	(0.001)	(0.001)	(0.000)
Int. Rate		-0.001***	-0.001***
		(0.000)	(0.000)
Log (Loan Amnt)		-0.007***	-0.007***
		(0.000)	(0.000)
Log(term)		0.006***	0.004***
		(0.000)	(0.000)
Log (Word count)		0.008***	0.005***
		(0.000)	(0.000)
Credit score	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
Education	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)
Log (Income)	0.001***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)
Log(EmpLength)	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
Vehicle	-0.010***	-0.006***	-0.003***
	(0.001)	(0.001)	(0.001)
Married	0.000	0.000	-0.001
	(0.001)	(0.001)	(0.001)
Log (Age)	0.051	0.079**	0.094***
	(0.037)	(0.034)	(0.028)
Log (Age^2)	-0.006	-0.010**	-0.012***
	(0.005)	(0.005)	(0.004)
Number of previous fails			-0.007***
			(0.000)
Pseudo R^2	0.93	0.94	0.94
N	371,872	371,872	371,872

Note: This table reports the marginal effects estimated around mean points from logit estimations. Clustered errors by borrower are in parentheses. Dependent variable is *Funded,* equal to 1 if lenders approve the application; zero otherwise. Column (1) presents results when we have borrower characteristics. Column (2) adds loan characteristics and column (3) adds information on the number of previously failed funding requests. *Female* equals to 1 if the borrower is female; 0 otherwise. *Int. Rate* is the rate of interest in percentages (%) that borrower is willing to pay. *Log(Loan Amnt)* is the log of loan amount requested by the borrower in thousand RMB. *Log(Term)* is the log of loan maturity in months. *Log(Word count)* is the log of word count of loan narrative posted by the borrower. *Credit score* is the credit score of the borrower (as of when the listing was created). *Education* equals to 1 if the borrower has at least a university degree. *Log(Income)* is the log of monthly income of the borrower. *Log(EmpLength)* is the log of work experience in number of years. *Vehicle* equals to 1 if the borrower has a car; 0 otherwise. *Marriage status* equals to 1 if the borrower is married; 0 otherwise. *Log(Age)* is the log of the age of borrower in years. *Log(Age^2)* is the log of borrower's age squared. *Number of previous fails* is the cumulative number of previous rejections. Industry and year dummies are included but not reported. ∗, ∗∗, ∗∗∗ denotes significance at the 10, 5 and 1% level.

Table 4. Borrowers' decision to apply or not.

	Failed first attempt (1)	Failed first two attempts (2)	Failed first three attempts (3)
Female	-0.018***	-0.021**	-0.015
	(0.005)	(0.009)	(0.015)
Int. Rate	0.000	0.009***	0.013***
	(0.000)	(0.001)	(0.002)
Log(Loan Amnt)	-0.008***	0.005*	0.009*
	(0.001)	(0.003)	(0.005)
Log(term)	0.0011***	-0.005	-0.018**
	(0.002)	(0.005)	(0.008)
Log(Word count)	-0.051***	-0.007	-0.005
	(0.003)	(0.005)	(0.008)
Credit score	0.006***	0.007***	0.006***
	(0.000)	(0.000)	(0.001)
Education	-0.006	-0.018**	-0.022*
	(0.004)	(0.009)	(0.013)
Log(Income)	0.026***	0.004	0.003
	(0.002)	(0.004)	(0.007)
Log(EmpLength)	-0.004**	0.004	0.000
	(0.002)	(0.004)	(0.006)
Vehicle	0.104***	0.029***	0.010
	(0.003)	(0.007)	(0.011)
Married	-0.015***	0.012*	0.002
	(0.003)	(0.007)	(0.011)
Log(Age)	1.175***	-0.021	-1.941***
	(0.196)	(0.435)	(0.713)
Log(Age^2)	-0.174***	-0.011	0.266***
	(0.028)	(0.063)	(0.102)
Pseudo R^2	0.05	0.03	0.02
N	84,362	24,461	10,226

Note: This table reports the marginal effects estimated around mean points. Clustered errors by borrower are in parentheses. Column (1), (2) and (3) represents marginal effects results after business borrowers failed first, first two and first three applications, respectively. Dependent variable is *applied*, equal to 1 if the borrower has submitted a loan application after experiencing one or more earlier rejection(s) and zero otherwise. *Female* equals to 1 if the borrower is female; 0 otherwise. *Int. Rate* is the rate of interest in percentages (%) that borrower is willing to pay. *Log(Loan Amnt)* is the log of loan amount requested by the borrower in thousand RMB. *Log(Term)* is the log of loan maturity in months. *Log(Word count)* is the log of word count of loan narrative posted by the borrower. *Credit score* is the credit score of the borrower (as of when the listing was created). *Education* equals to 1 if the borrower has at least a university degree. *Log(Income)* is the log of monthly income of the borrower. *Log(EmpLength)* is the log of work experience in number of years. *Vehicle* equals to 1 if the borrower has a car; 0 otherwise. *Marriage status* equals to 1 if the borrower is married; 0 otherwise. *Log(Age)* is the log of the age of borrower in years. *Log(Age^2)* is the log of borrower's age squared. Industry and year dummies are included but not reported. ∗, ∗∗, ∗∗∗ denotes significance at the 10, 5 and 1% level.

Table 5. Results for subsamples.

Panel A: Lenders' decision to approve or not.

	Loan Use		Regional Development	
	Working capital	Fixed investment	High	Low
	(1)	(2)	(3)	(4)
Female	0.002***	0.003***	0.000	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
R2	0.94	0.94	0.95	0.93
N	321,761	50,111	167,702	204,170

Panel B: Borrowers' decision to apply or not after the first failed attempt.

	Loan Use		Regional Development	
	Working capital	Fixed investment	High	Low
	(1)	(2)	(3)	(4)
Female	-0.019***	-0.015	-0.025***	-0.016***
	(0.005)	(0.009)	(0.008)	(0.005)
R2	0.05	0.06	0.05	0.06
N	65,516	18,842	25,290	59,072

Note: This table reports the marginal effects estimated around mean points after logit estimations. Clustered errors by borrower are in parentheses. Panel A reports results for lenders' decision to approve loans or not, while Panel B presents results for borrowers' decision to apply or not. Both panels include the full set of control variables as reported in notes for Tables 3 and 4. ∗, ∗∗, ∗∗∗ denotes significance at the 10, 5 and 1% level.

Table 6. Propensity score matching.

	Borrowers' decision to apply or not			Lenders' decision to approve or not		
	Failed first attempt (1)	Failed first two attempts (2)	Failed first three attempts (3)	All (4)	2012 – 2014 (5)	2012 – 2018 (6)
Female	-0.012**	-0.022**	-0.006	0.007**	0.011	0.009**
	(0.005)	(0.011)	(0.021)	(0.002)	(0.006)	(0.002)
Matched N	31,294	8,930	2,484	371,872	112,421	366,711

Note: In this table, we 1:1 match male and female applicants and report the average treatment effects of *Female* (the treatment) on borrowers' decision to apply or not in Panel A and on lenders' decision to approve or not in Panel B. In Panel A, the dependent variable is *applied* (= 1 if the borrower has submitted a loan application after experiencing earlier rejection(s); zero otherwise). Column (1), (2) and (3) represents results after borrowers failed first, first two and first three applications, respectively. *Female* equals to 1 if the borrower is female; 0 otherwise. We include all the variables on loan terms and borrower characteristics. *Int. Rate* is the rate of interest in percentages (%) that borrower is willing to pay. *Log(Loan Amnt)* is the log of loan amount requested by the borrower in thousand RMB. *Log(Term)* is the log of loan maturity in months. *Log(Word count)* is the log of word count of loan narrative posted by the borrower. *Credit score* is the credit score of the borrower (as of when the listing was created). *Education* equals to 1 if the borrower has at least a university degree. *Log(Income)* is the log of monthly income of the borrower. *Log(EmpLength)* is the log of work experience in number of years. *Vehicle* equals to 1 if the borrower has a car; 0 otherwise. *Marriage status* equals to 1 if the borrower is married; 0 otherwise. *Log(Age)* is the log of the age of borrower in years. *Log(Age^2)* is the log of borrower's age squared. In Panel B, the dependent variable is *funded*, equal to 1 if lenders approve the application; zero otherwise. Column (4), (5) and (6) presents the results for the time periods of 2010 – 2018, 2012 – 2014 and 2012 – 2018, respectively. We include all the variables on loan terms and borrower characteristics and the information on the number of previous failed funding requests. ∗, ∗∗, ∗∗∗ denote significance at the 10, 5 and 1% level.