Ladies First:

Female Entrepreneurs Gaining Ground in Fintech Credit Access

Marshall Xiaoyin Ma
Fudan University
Email: maxy@fudan.edu.cn

Sipeng Zeng
Cheung Kong Graduate School of Business
Email: spzeng-bp@ckgsb.edu.cn

Xiaobo Zhang
Peking University
Email: x.zhang@gsm.pku.edu.cn

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Abstract

In developing countries, female entrepreneurs generally face greater challenges than their male counterparts in accessing traditional bank credit. This paper demonstrates that this disadvantage has been reversed in the fintech era in China. Using a unique dataset of Online Survey of Micro-and-small Enterprises (OSOME) spanning 12 consecutive quarters, combined with real business data of digital credit scores and after-loan transactional cash flow, we present two stylized facts about the female premium in online credit access: (i) Micro and small enterprises (MSEs) owned by female entrepreneurs are 4.9% more likely to receive an online loan, even after controlling for application selection bias and (ii) Interest rates for online loans granted to female entrepreneurs are, on average, 30 basis points lower than those granted to their male counterparts. Notably, the female premium in online financing is not observed in offline loans. The female premium in access to online credit is substantially explained by their superior digital creditworthiness, as proxied by the Sesame Credit Score. Furthermore, our results show that receiving online credit boosts the one-year survival rate of MSEs by 3.3% and increases operating income by 31% regardless of gender.

Keywords: Gender; Credit Access; Fintech; Micro and Small Enterprises

JEL: G21; G23; G32; G41

1. Introduction

Despite findings that female-owned businesses exhibit lower default rates than those owned by men (De Andrés et al., 2021; Delis et al., 2022), female entrepreneurs lack a comparative advantage when applying for loans (Asiedu et al., 2012; Alesina et al., 2013; Moro et al., 2017). They frequently encounter barriers to bank credit due to implicit discrimination (Beck et al., 2018; De Andrés et al., 2021), which often discourages them from applying altogether (Treichel and Scott, 2006; Ongena and Popov, 2016). Ultimately, this credit gap contributes to women's lower rates of participation in entrepreneurial ventures overall (Ongena and Popov, 2016; Beck et al., 2018; De Andrés et al., 2021).

The rise of fintech presents a promising solution to the systemic disadvantages faced by female entrepreneurs. Fintech lenders use big data, such as social media activity (Jagtiani and Lemieux, 2019) and users' digital footprints (Berg et al., 2020), as a substitute for traditional collateral (Gambacorta et al., 2022). This enables a more comprehensive assessment of creditworthiness, leveling the playing field for women. While women generally possess less collateral than men, they tend to exhibit superior "digital creditworthiness," potentially providing them an edge in the fintech era.

To test this idea, we utilize a unique dataset of Online Survey of Micro-and-small Enterprises (OSOME) in China (Kong et al., 2022), covering 12 consecutive quarters. The survey is matched with granular business data from the Alipay platform, including transactional cash flow and digital credit metrics such as the Sesame Credit Score[1], consumer loan delinquency information, and online business loan origination.

Our analysis of the digital creditworthiness data reveals that 51.8% of female entrepreneurs achieve an "excellent" Sesame Credit Score (exceeding 700 points), compared to only 43.5% of men. Furthermore, female entrepreneurs are 2.3 percentage points less likely to have overdue records on Ant Group consumer loans and 2.5 percentage points more likely to be approved for business loans.

[1] The *Sesame Credit Score* is measured by the Sesame Credit Management Co., Ltd., a third-party credit score company affiliated with Alipay. It assesses an individual's overall credit risk largely based on digital footprints concerning about credit history, behavioral preferences, repayment capabilities, personal characteristics, and social networks.

Our OSOME survey data confirms, from a broader set of credit providers (not limited to Ant loans), that female entrepreneurs consistently enjoy higher approval rates for online loans across the sample period. Notably, they receive interest rates that are, on average, 58 basis points lower than those for men — an advantage entirely absent in offline lending. These objective findings are further corroborated by entrepreneurs' own subjective assessment of credit accessibility.

This improved access significantly impacts the intensive margin of business operations. Among entrepreneurs previously rejected for offline credit, receiving an online loan increased survival rates by 3.3% and operating income by 31% after one year. Even as a lower-bound estimate, this added survival rate translates to approximately 1.39% of China's total workforce.

Beyond the intensive margin, the "female premium" in online credit access likely boosts the extensive margin of female entrepreneurship. As shown in Cong et al. (2024a), female entrepreneurship has surged alongside China's rapid digital transformation. Enhanced access to online credit may have empowered more potential female entrepreneurs, thereby driving a rise in female entrepreneurship.

In addition to directly addressing the literature on gender differences in access to credit, our paper also contributes to the literature on financial inclusion. Promoting the financial inclusion of these enterprises has long been a challenge for policymakers worldwide (Vos et al., 2007; Abdulsaleh and Worthington, 2013; Huang et al., 2016). Due to high costs, physical distance, and stringent bank regulations (Agarwal and Hauswald, 2010; Demirgüç-Kunt and Klapper, 2013), access to traditional bank credit for MSEs in developing countries remains limited (Banerjee et al., 2015; Demirgüç-Kunt et al., 2020; Hau et al., 2024).

Our paper demonstrates data-driven fintech lending offers a viable, low-risk channel for reaching underrepresented groups (Liu et al., 2022). This suggests that in developing regions, prioritizing fintech infrastructure may be more effective than attempting to overhaul traditional financial systems (Hjort and Poulsen, 2019).

Our paper also relates to the literature on how algorithms can mitigate systematic

discrimination against certain groups of people in traditional bank lending (Howell et al., 2024). While previous studies have focused on racial disparities in developed economies, we focus on gender in developing countries. Moreover, our work is distinguished by its inclusion of a large sample of self-employed and unregistered business entities often overlooked in the literature due to data scarcity.

The remainder of the paper is organized as follows. Section 2 provides the institutional background on MSEs, online and offline loans, and hypotheses. Section 3 describes the data and outlines our empirical strategy. Section 4 presents the empirical results of our key findings. Section 5 reports on investigations into the potential mechanisms and the welfare impacts. The last section summarizes the main conclusions.

2. Institutional Background and Hypothesis Development

2.1 Micro and Small Enterprises in China

The micro and small enterprises (MSEs) studied in this paper are smaller in scale than the small and medium-sized enterprises (SMEs) typically examined in the existing literature (e.g., Huang et al., 2023; Beaumont et al., 2021; Ben-David et al., 2021). Our research specifically targets micro-enterprises, which generally employ fewer than 10 individuals. Approximately 90% of our sample consists of self-employed businesses, half of which are unregistered. We classify these entities using the 2011 Enterprise Classification Standard issued by China's Ministry of Industry and Information Technology.[2]

Despite their small scale, MSEs are fundamental pillars of the economy, generating 60% of GDP and accounting for approximately 80% of total employment. MSEs constitute over 90% of all registered market entities in China.[3] The inclusion of unregistered self-employed businesses—such as kiosks and street-side restaurants—suggests an even more dominant presence. Because these businesses often lack

[2] See Appendix Table A2 for detailed classification criteria.

[3] In the People's Republic of China, "individual industrial and commercial households" refer to self-employed persons using personal or family assets as capital. These are legally registered and categorized as MSEs. However, our sample also includes a significant volume of unregistered self-employed businesses that operate outside these formal forms.

traditional collateral or financial records, their financing needs have historically been overlooked in academic research (Cong et al., 2024b). Our study aims to fill this critical gap by providing empirical evidence on credit access for this "invisible" segment of the economy.

2.2 Online and Offline Lending

In this paper, "online lending" or "online loans" refers to credit products where the *entire* loan application, underwriting, and disbursement process is completed online. These loans are primarily issued by internet banks and other fintech lenders.[4] We also classify loans from traditional banks as "online" if they involve no manual intervention and are approved automatically via algorithmic assessment.

Conversely, "offline lending" or "offline loans" include loans that require at least one in-person step, such as a physical branch visit, document signing, or site inspection. These are typically provided by traditional commercial banks.

Approximately 98% of online loans are unsecured, a significantly higher proportion than found in offline lending (Liu et al., 2022). The digital-only nature of online applications makes it difficult for financial institutions to verify physical collateral for MSEs, necessitating a shift in risk assessment.

As an alternative, online lenders use unconventional data, such as digital footprints, to evaluate creditworthiness, especially for borrowers with limited traditional credit histories (Berg et al., 2020; Di Maggio et al., 2022). In contrast, many traditional banks have limited access to this unconventional data, which makes it challenging for them to incorporate it into their legacy credit risk models (Gambacorta et al., 2022).

Because internet banks and other fintech lenders typically do not take deposits, they frequently operate under different regulatory frameworks. This provides them with more discretionary power to employ machine learning algorithms and unconventional data for credit risk assessment (Liu et al., 2022). Traditional banks face more stringent regulatory restrictions regarding the use of individual entrepreneur information when

[4] In this paper, "other fintech lenders" refers to non-bank entities that lend to MSEs primarily through online channels, the vast majority of which utilize fully automated, computer-driven approval processes (Allen et al., 2021).

assessing MSE business loans (Huang et al., 2023).

2.3 Hypothesis Development

Assessing the credit risk of MSEs for traditional loans is inherently difficult due to their limited collateral and scant financial histories. Traditional banks heavily rely on credit officers to evaluate the status of MSEs, a process through standardized assessment forms that prioritize tangible assets.

As illustrated by the credit assessment form from a Chinese state bank (see Appendix Figure A1), the evaluation focuses on enterprise assets and performance, alongside business owners' characteristics, such as family assets, liabilities, and credit history. The China Banking and Insurance Regulatory Commission mandates strict due diligence, requiring that credit risk assessments be based strictly on the information provided in the credit assessment form.

Although creditors may use their professional judgement to assess risk (Berger and Udell, 2002, 2006), making decisions based on unlisted factors, such as gender, carries significant regulatory risk. Consequently, female entrepreneurs rarely gain an advantage in traditional banking. Given that women normally have fewer physical and financial assets under their names than men, they are often at a distinct disadvantage when seeking traditional bank loans.

The dominant role of collaterals in traditional lending leaves a wealth of valuable information untapped. In contrast, fintech lenders—including internet banks and technology firms—address this gap by feeding digital footprints into machine learning algorithms to calculate credit risk (Liu et al., 2022). These algorithms identify patterns in historical data, frequently revealing that women are less likely to default on credit than men.

Existing literature supports this: De Andrés et al. (2021) and Delis et al. (2022) find that female-led businesses in Spain and the United States exhibit lower default rate. Similarly, Chen et al. (2020) find that female peer-to-peer borrowers in China are less likely to default. Economically, lower credit risk should be translated into lower risk

premiums (Mishkin and Eakins, 2019).

In the Chinese context, our analysis of the Alipay platform data corroborates these trends. As shown in Figures 1 and 2, female entrepreneurs possess higher Sesame Credit Scores, lower overdue probabilities, and higher business loan approval rates than their male counterparts.[5] Based on these facts, we formulate the following hypotheses to investigate the gender premium in loan originations, loan pricing, and the underlying mechanisms:

Hypothesis 1 (H1): Ceteris paribus, female entrepreneurs are more likely to obtain loans from online financial institutions than male entrepreneurs.

Hypothesis 2 (H2): Ceteris paribus, female entrepreneurs receive lower interest rates on online loans than male entrepreneurs.

Hypothesis 3 (H3): Ceteris paribus, the superior digital creditworthiness of female entrepreneurs serves as a primary channel for their online loan origination premium.

3. Data and Research Design

3.1 Online Survey of Micro-and-small Enterprises Data

Our analysis utilizes data from the Online Survey of Micro-and-small Enterprises (OSOME). The quarterly survey, jointly conducted by Peking University and the Ant Group Research Institute, focuses on owners of small enterprises and self-employed businesses, who are active users of Alipay, China's leading mobile payment platform (Dai et al., 2021; Kong et al., 2022).[6]

Alipay is a massive platform, reporting over 1.2 billion monthly users in 2019 and serving as the preferred payment method for 90% of urban residents in China (Klein, 2020; Cong et al., 2024b).[7] Its reach extends beyond e-commerce to facilitate offline business transactions and remittances, with a user base that closely aligns with the Chinese population aged 16-59 (Bian et al., 2023). To ensure privacy, survey data was

[5] See the next section for data details.

[6] Active self-employed businesses on the Alipay platform are defined as those that conducted transactions for at least three months within the past 12 months, with a total transaction volume exceeding 2,000 RMB and involving more than 90 transactions.

[7] Refer to www.xinhuanet.com/english/2019-10/01/c_138440413.htm.

anonymized and analyzed remotely via the Ant Open Research Laboratory Platform. This secure sandbox environment allows researchers to conduct statistical analyses while preventing access to individual observations. All survey respondents authorized the use of their data for academic research.

The quarterly survey was randomly distributed to MSE owners who actively utilize the Alipay application for payments.[8] A survey link was featured in the primary message box on application's first tab, a high-visibility location typically reserved for system notifications such as transaction reminders and utility bills.

The survey covered five primary domains: business operations, credit usage, financial health, personal demographics, and business outlook. Conducted over 12 consecutive quarters from 2020Q3 to 2023Q2, this dataset provides unique, high-frequency data for documenting loan applications and approvals among small and micro business operators in China.[9] From the initial dataset, we excluded 7,283 observations categorized as medium-size firms according to the Enterprise Classification Standard (see Appendix Table A2). Our final research sample comprises 131,106 observations.[10]

3.2 Alternative Digital Creditworthiness and Transactional Cash Flow Data

To explore the mechanism and welfare impacts of the "female premium" in online lending, we matched the OSOME questionnaire data with a unique set of digital creditworthiness metrics from Ant Group's business operations. For survey respondents with active credit and business records on the Alipay platform, we obtained four key data elements: (1) Sesame Credit Scores, (2) overdue history of Ant consumer credit,[11] (3) approval status for Ant business loans, and (4) transactional cash flow data. We successfully matched a total of 103,387 observations.

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[8] The Alipay platform is owned by Ant Group, a leader in financial services specializing in MSEs and individual consumers. As of June 2022, the company had disbursed more than 2 trillion RMB in loans. Note that OSOME respondents are Alipay users but not necessarily Ant Group borrowers.

[9] The demographic profiles (age, education, and industry) of these business owners are consistent with those in the onsite Enterprise Survey for Innovation and Entrepreneurship in China (ESIEC).

[10] Analysis including these medium-sized enterprises yielded similar results. To maintain focus and save space, these results are omitted here but are available upon request.

[11] Ant Group provides a revolving consumer credit limit. An account is marked as overdue if a repayment is delayed by more than one month.

The Sesame Credit Score assesses an individual's overall credit risk using a variety of variables derived from digital footprints, including credit history, behavioral preferences, repayment capability, personal characteristics, and social networks. Modeled after the FICO score in the United States, a higher Sesame Credit Score indicates superior credit status and a lower likelihood of default. Scores are generally segmented as: 350–550 (poor), 550–600 (moderate), 650–700 (good), and 700–950 (excellent). [12]

Ant Group relies heavily on this score for its automated monthly credit assessments. Hau et al. (2024) note that before 2015, Ant Group used a threshold of 480 points to determine whether to approve a credit application or not, although other factors are also considered. While the current approval algorithm for credit approval may have evolved, the Sesame Credit Score remains the primary determinant of credit eligibility. Because these scores are widely used both within and outside the Alipay system (e.g., as for visa applications), they serve as a robust measure of an individual's overall digital creditworthiness.

Figure 1 presents the distribution of Sesame Credit Scores of entrepreneurs by gender. It can be observed that female entrepreneurs consistently outperform their male counterparts. Specifically, 51.8% of women achieve an "Excellent" score (exceeding 700 points), compared to 43.5% of men. Conversely, only 2.9% of women fall into the "Poor" category (lower than 550 points), compared to 4.2% of men.

[Figure 1 about here]

Figure 2 highlights the overdue status of personal consumer loans and the approval rates for business loans issued by Ant Group for both female and male entrepreneurs. Female entrepreneurs are 2.3 percentage points more likely to have a non-overdue credit record and 2.5 percentage points more likely to receive business loan approval than their male counterparts. These results collectively indicate that female

[12] The Sesame Credit Score data we obtained are segmented ordinal variables. For analysis, we coded them as follows, 1 represents scores in [350, 550), 2 for [550, 600), 3 for [600, 650), 4 for [650, 700), 5 for [700, 750), 6 for [750, 800), and 7 for [800, 950].

entrepreneurs in our sample possess higher digital creditworthiness than men.

[Figure 2 about here]

The transactional cash flow data allows us to evaluate the post-loan performance of entrepreneurs who receive payment via QR codes or Alipay transfers. Given high user loyalty and Alipay's dominant market share, we use these transaction volumes as a reliable proxy for real business revenue.[13]

Our dataset offers three distinct advantages over traditional credit studies. First, unlike studies relying on data from a single bank (e.g., Adams and Ferreira, 2009; Iyer and Puri, 2012; Berg, 2018; Delis et al., 2022), our demand-side data includes outcomes from various institutions—traditional banks, microfinance firms, and online lenders—making it more representative of the broader credit market.

Second, linking overall loan application data from OSOME with real transactional footprints provides a unique opportunity to test the mechanism behind the gender premium and measure the resulting welfare effects.

Third, supply-side data often ignores firms that do not apply for loans due to anticipated rejection. Our sample includes MSEs that have not applied for credit, allowing us to mitigate sample selection bias using a Heckman two-stage model.

Micro-and-small entrepreneurs are categorized into four mutually exclusive groups based on their application behavior (See Table 1): (1) those who did not apply for loans, (2) those who applied for only online loans, (3) those who applied for only offline loans, and (4) those who applied for both online and offline loans. We also constructed four samples for analysis: (1) those who applied for online loans, (2) those who applied for offline loans, (3) those who applied for loans, and (4) those who applied for a loan in either online or offline mode. Approximately 56.6% of the sample applied for loans. Of these, 46.3% applied for online loans and 24.4% applied offline.

[Table 1 about here]

[13] Alipay and WeChat QR codes account for over 90% of offline payment scenarios in China (https://www.sixthtone.com/news/1009368). Alipay is the leading payment platform for online trade (https://www.enterpriseappstoday.com/stats/alipay-statistics.html).

As Figure 3 shows, male entrepreneurs apply for credit at a higher rate than female entrepreneurs across all categories, resulting in a total application rate roughly 7% higher for men. This aligns with existing research suggesting that female entrepreneurs are generally more risk-averse and less willing to increase their debt, compared to their male counterparts (Carter et al., 2007; Dawson and Henley, 2015).

[Figure 3 about here]

3.3 Research Design

To examine gender differences in loan applications and originations, we first employ a Logit regression for the full sample:

$$\Phi(Y_{i,t})=\beta_0+\beta_1 Female_i+\boldsymbol{X_{i,t}}\boldsymbol{T}+\boldsymbol{Z_i}\boldsymbol{\Lambda}+\delta_p+\delta_{q\times ind}+\epsilon_{i,t} \quad \text{Eq. (1)}$$

Where Φ is logit function; the dependent variable $Y_{i,t}$ is one of the following binary outcomes:

- *Apply(online)*: A binary variable equal to 1 if entrepreneur *i* applies for an online loan in quarter *t*, and 0 otherwise.
- *Apply(offline)*: A binary variable equal to 1 if entrepreneur *i* applies for an offline loan in the quarter *t*, and 0 otherwise.

The key variable of interest is *Female*, a dummy variable equal to 1 if the entrepreneur *i* is female, and 0 otherwise. We include control variables at two levels. At the enterprise level (*X*), we include revenue, profit margin, length of time that cash flow could sustain operations (*Cash holdings*), the length of the enterprise's existence (*Firm age*), the proportion of the enterprise's online sales to total sales (*Online sales*), and number of employees (*Employee*). At the individual level (*Z*), we consider age (*Age*) and higher education status (*Higher education*) as control variables, reflecting information commonly required in loan applications. All specifications include province (δ_p) and quarter×industry dummy variables $\delta_{q\times ind}$.

To quantify the potential "female premium" in accessing online credit, we further

run the following Difference-in-Differences (DiD) model among the subsample of individuals who applied for a loan:

$$Granted_{i,t}=\beta_0+\beta_1 Female_i \times Online_i+\beta_2 Female_i+\beta_3 Online_i+\boldsymbol{X_{i,t}}'\boldsymbol{\Gamma}+\boldsymbol{Z_i}'\boldsymbol{\Lambda}+\delta_p+\delta_{q\times ind}+\epsilon_{i,t}$$

Eq. (2)

In this model, $Granted_{i,t}$ is a binary variable indicating loan approval. $Online_i$ is a dummy variable indicating whether the loan application was submitted online or not. The coefficient β_1 captures the differential impact of being female on the likelihood of approval for online versus offline loans.

To test Hypothesis 1, we estimate the probability of loan disbursement by loan type for female and male entrepreneurs using the following specification:

$$P\left(Granted_{i,t}=1\middle|Apply_{i,t}=1\right)=\alpha_1+\beta_1 Female_i+Controls+\epsilon_{i,t}$$

Eq. (3)

The control variables are the same as in Equations (1) and (2). We estimate this model separately for Granted (online) and Granted (offline) to compare approval probabilities across genders.

To test Hypothesis H2, we replace the dependent variable in Equation (1) with the loan interest rate to examine gender-based pricing differentials. To test Hypothesis H3, we augment Equation (1) by including digital creditworthiness, proxied by the Sesame Credit Score, to observe if digital footprints mitigate gender gaps.

3.4 Summary Statistics

Table 2 presents the summary statistics for the variables used in this paper. Panel A reports the pooled summary statistics, showing higher approval rate for online loan applications (82.1%) compared to offline loan applications (70.5%). The proportion of female entrepreneurs in our sample varies from 16% to 25% across survey rounds. This is consistent with the findings of Cong et al. (2024a), who documented a rise in female entrepreneurship from 16.4% in 1995 to 27.4% in 2020. On average, micro-and-small entrepreneurs are 33 years old; 53.7% are married, and 39.9% hold a college or university degree.

Panel B compares these statistics by gender. Male entrepreneurs typically manage their businesses with higher revenues, profit margins, and cash flows. Demographically, male entrepreneurs in the sample are younger, less likely to be married, and possess slightly lower levels of education compared to their female counterparts. These differences are statistically significant at the 1% level, as confirmed by *t*-test results.

Regarding credit behavior, female entrepreneurs are less likely to apply for loans. However, conditional on applying, female entrepreneurs exhibit a higher probability of loan approval, secure lower interest rates, and report fewer financing difficulties for online loans compared to male entrepreneurs. Notably, these gender-based advantages are absent in the offline loan market. Finally, the intensity of digital engagement, as measured by the proportion of online sales to total sales, is marginally higher for female entrepreneurs than for their male counterparts.

[Table 2 about here]

4. Empirical Results

4.1 Gender Differences in Loan Application

Table 3 reports the Logit regression results concerning gender differences in loan application and approval from Equations (1) and (2). Columns (1) and (2) include the full sample of survey respondents, where the dependent variables are binary outcomes of credit application and online credit application of an entrepreneur *i* in the quarter *t*. Based on the average marginal effects (AME) derived from the regression coefficients, female entrepreneurs are 4.4% less likely to apply for any credit loan and 3.8% less likely to apply for an online credit loan compared to the male counterparts.[14] Regarding control variables, revenue, online sales ratio, and education levels are significantly and positively correlated with the probability of applying for a loan. Similarly, profit margin, cash holdings, firm age, and entrepreneur age show significant positive correlation with application likelihood.

[14] The table reports the regression coefficients of the Logit model. The average marginal effects are calculated using the equation: $\frac{\partial p}{\partial x_j} = \sum_{i=1}^{N} \Phi(X_i{}'\beta)\beta_j / N$, where $X_i{}'$ denotes a regressor vector, β is a K×1 parameter vector, β_j is the regression coefficient for the variable of interest, and N is the sample size.

[Table 3 about here]

4.2 Loan Approval and the "Female Premium"

Table 4 reports the baseline results from Equation (3), focusing on approval probabilities. As shown in column (2), there is no significant gender difference in the approval of offline loan applications. However, among online loan applicants, female entrepreneurs are significantly more likely to be approved than male entrepreneurs, as indicated in column (1).

When merging the samples and utilizing an interaction term (Female×Online), the coefficient is significantly positive at the 10% level. This suggests that female entrepreneurs enjoy a comparative advantage in obtaining credit through online channels relative to traditional offline institutions. Notably, while online sales intensity increases the likelihood of online approval, it is negatively associated with offline approval. Furthermore, higher education significantly boosts the probability of receiving an online loan but has no significant impact on offline loan outcomes.

[Table 4 about here]

4.3 Addressing Selection Bias

Fintech institutions leverage digital footprints to assess credit risk, which is particularly advantageous for borrowers lacking formal financial history or collateral (Holmström, 2018; Huang et al., 2023). However, the observed gender gap in approval rates could potentially be driven by self-selection: highly qualified female entrepreneurs might opt for online loans specifically to circumvent face-to-face discrimination at traditional banks. Such selection bias may stem from two primary sources: the entrepreneurs' internal preferences and external discrimination from traditional financial institutions.

To address these concerns, we employ two distinct empirical strategies. First, we isolate the potential bias from traditional banks by analyzing a subsample of entrepreneurs who submitted both online and offline loan applications. This ensures

that the same pool of applicants is being reviewed by both internet banks and traditional banks, allowing us to isolate the institutional decision-making process from applicant self-selection.

As illustrated in Figure 4, the offline approval rate is nearly identical across genders (67%–68%). In contrast, the online loan approval rate for women was 82%, compared to 79% for men, showing a raw "female premium" of 3 percentage points. Figure 5 demonstrates that this premium is persistent across all 12 quarters, ranging from 0.8% to 6.1%.

[Figure 4 about here]

[Figure 5 about here]

While these raw comparisons are revealing, they do not account for individual, regional, and industry characteristics. Therefore, we incorporate these controls in OLS regressions in Table 4. As shown in Columns (4) and (5), female entrepreneurs remain 3.2% more likely to be granted an online loan than their male counterparts. Conversely, no significant gender difference in the approval rate exists for offline loan applications. These findings provide preliminary support for Hypothesis H1.

Despite controlling for observable characteristics, a latent selection problem remains: some female entrepreneurs may opt out of the credit market entirely due to risk aversion or lack of confidence (Byrnes et al., 1999; Croson and Gneezy, 2009). To address this, we employ a Heckman two-stage model, using the number of children in the household as the instrumental variable in the first-stage selection equation (Gronau, 1973; Heckman, 1974). Families with children typically face higher financial commitments (Lobel and Clair, 1992; Fang et al., 2022) and thus are more likely to seek external financing for family-run micro-and-small businesses. Crucially, the number of children is not standard information required for loan processing and should not inherently influence a bank's loan approval decision.

Because only some survey quarters contained questions about the number of children, the sample size for this analysis is reduced to 39,640. Panel A of Table 5

reports the first-stage results. As anticipated, the number of children positively influences an entrepreneur's decision to apply for credit. Columns (2) and (3) also indicate that female entrepreneurs are generally less likely to apply for a loan. Interestingly, while female entrepreneurs are 3% less likely than men to apply for offline loans, there is no significant gender difference in online loan applications. This parity suggests that the digital environment may mitigate the "reluctance" or suspicion female entrepreneurs often feel toward traditional creditors (Ghosh et al., 2018).

In the second stage, we incorporate the inverse Mills ratio estimated from the first stage (Panel B of Table 5). Following this adjustment, female premium actually increases from the raw 3 percentage points to 4.9% after accounting for self-selection bias, while the gender gap for offline loans remains non-significant.

Finally, to ensure the validity of our identification strategy, we regressed online sales on the number of children (Table A3). We found that online sales revenue is negatively correlated with the number of children, regardless of gender. This alleviates concerns that entrepreneurs with more children might simply engage in more online activity, thereby leaving larger digital footprints that bias the results.

[Table 5 about here]

4.4 Female Advantage in Accessing Online Credit among "Long-tail" Borrowers

A central question in the digital finance literature is whether fintech expands credit access to "long-tail" customers, those traditionally underserved or excluded by conventional offline lenders. To address this, we compare the role of gender in securing online loans across two distinct subsamples of applicants using a Logit model consistent with our baseline specification.

First, we compare two groups of entrepreneurs who applied both offline and online loans, categorized by their offline approval status. As shown in Column (1) of Table 6, gender has little to do with the probability of online loan approval within this "credit-proven" group (those who successfully secured offline loans). Second, we examine the subsample of applicants who were denied offline loans. As shown in Column (2), the

coefficient for the female variable is 0.293, which is statistically significant at the 1 % level. Calculated as an average marginal effect, this indicates that among entrepreneurs rejected by traditional banks, women are 4.0% more likely to receive an online loan than their male counterparts.

These results suggest that the “female premium” is most pronounced among “long-tail” customers, who are overlooked by traditional offline institutions. This aligns with recent evidence that fintech platforms specifically target segments where credit demand remains unmet by the traditional sector (Tang, 2019; Gambacorta et al., 2022; Liu et al., 2022). Essentially, the online lending market serves as a vital compensatory mechanism or a “second-chance” provider for female entrepreneurs who may be subject to implicit biases or overly stringent criteria in the traditional lending sector. Our findings underscore that the extensive growth margin of online credit is a critical driver of financial inclusion for women.

[Table 6 about here]

4.5 Gender and Business Performance

While we have demonstrated a female premium in online credit access and hypothesized that it is primarily due to their superior digital footprints, an alternative explanation exists: female entrepreneurs might possess superior business skills that online lenders are better positioned to recognize than traditional lenders. This "superior talent" channel could theoretically account for the higher approval rates observed for women in the digital space. To test the viability of this channel, we investigate the relationship between gender and business operational performance. We employ ordinary least squares (OLS) regressions using three key business performance indicators—revenue, profit margin, and cash holdings—as dependent variables, with gender as the primary independent variable. The results are presented in Table 7.

The coefficients for the female variable are negative and statistically significant across all specifications, indicating that female entrepreneurs generally underperform their male counterparts across these metrics. Specifically, among those who

successfully obtained online loans, female-led enterprises have, on average, 28.2% lower business revenues, 1.3 percentage points lower profit margins, and 26.3% lower cash holdings, than male-led enterprises. In other words, female entrepreneurs enjoy a higher rate of loan approval despite having objectively weaker business performance metrics. These findings suggest that female entrepreneurs in our sample are not necessarily more adept at business management than their male counterparts. Consequently, it is unlikely that the observed female premium in online credit access is driven by superior entrepreneurial talent. This further reinforces the likelihood that the advantage is rooted in other factors, such as digital creditworthiness.

[Table 7 about here]

4.6 Gender and Loan Interest Rates

This subsection tests our second hypothesis: female entrepreneurs receive lower interest rates on online loans than their male counterparts. For this analysis, we use the raw annualized lending rate (Loan rate). Since the risk-free rate primarily varies over time, our use of quarter-industry fixed effects effectively controls for these variations. Figure 6 illustrates the distribution of online and offline loan rates by gender. As shown in Figure 6a, about 35% of female entrepreneurs received online loans with interest rates between 0% and 5%, compared to 31% of male entrepreneurs. In contrast, the gender gap for offline loans is much smaller: the proportion of female entrepreneurs receiving rates in the 0% to 5% bracket is only 1.7 percentage points higher than that of males (Figure 6b). This provides preliminary evidence that favorable interest rate disparities are more pronounced in the online lending market.

[Figure 6 about here]

Because loans with a 0% interest rate are typically government-subsidized loans and do not reflect an institution's market-based risk assessment, we exclude these observations from the OLS regressions. Table 9 presents the relationship between gender and loan interest rates. The results in Column (1) indicate that female

entrepreneurs obtain online loans at rates 58 basis points (bps) lower than male entrepreneurs. Conversely, Column (2) shows no significant gender difference in offline loan rates. The interaction model in Column (3) further confirms this "female premium"; female entrepreneurs secure online loans at an interest rate 30 bps lower than their male counterparts. This reduction is economically significant, representing a 3.7% decrease relative to the sample mean online interest rate of 8.2%. To partly ameliorate the concerns that these results are driven by selection bias, we repeat the analysis in Columns (4) and (5) using the subsample of entrepreneurs granted both online and offline loans. Within this controlled group, which is less susceptible to selection bias of traditional banks, female entrepreneurs continue to benefit from lower interest rates on online loans, while enjoying no such premium in the offline market. These findings strongly support Hypothesis H2.

[Table 8 about here]

5. The Potential Mechanism and Welfare Impact

5.1 Gender, Credit Score and Credit Access

This subsection assesses the extent to which the Sesame Credit Score—a metric derived from digital footprints—explains the online credit preferences and advantages observed for female entrepreneurs. Following the empirical strategy outlined in Section 3.2, we employ a Linear Probability Model (LPM) for this analysis. The choice of LPM over a Logit model is dictated by the categorical nature of the credit score variable and the technical constraints of the cloud-based Python environment provided by Ant Group's internal data.[15] Column (1) of Table 9 reports the regression of the Sesame Credit Score on gender. The results echo the descriptive findings in Figure 1: female entrepreneurs possess, on average, significantly higher Sesame Credit Scores than their male counterparts. This confirms that female entrepreneurs in our sample have a lower

[15] Due to the sensitivity of Ant's internal data of credit score and real business activities, we were granted a limited access to a cloud-based Python working environment that prevented us from implementing standard error adjustments. Therefore, we chose the AbsorbingLS method for estimation to retain the clustered adjustment of the standard errors. The Logit model also yields consistent results for columns 2-4 when a dichotomous variable is used as a dependent variable, even without adjusting the standard errors.

prior default risk as measured by their digital activity.

[Table 9 about here]

Column (2) tests gender differences in the probability of obtaining an Ant-specific business loan. The results indicate that the probability of approval is 3% higher for female entrepreneurs, a magnitude that aligns closely with our baseline findings and confirms the robustness of the "female premium".

In Column (3), we incorporate the Sesame Credit Score in the regression as a control variable. Upon this inclusion, the coefficient for the female variable becomes slightly negative (-0.007) and loses its statistical significance. Meanwhile, the coefficient for the Sesame Credit Score is 0.182 with a *t*-value of 58. By comparing the results of these two columns, it is apparent that the premium women enjoy in securing Ant business loans is entirely mediated by their demonstrably higher credit scores. Once digital creditworthiness is accounted for, the gender gap is eliminated, providing strong support for Hypothesis H3.

Finally, we study whether the Sesame Credit Score—as a proxy for general digital creditworthiness—explains the female premium across the broader online lending market. We focus on the subsample of applicants who applied for both online (from any institution, not exclusively from Ant Group) and offline loans. As shown in Column (5), the female premium remains positive but drops to 2%, representing a 26% decrease in magnitude compared to the result in Column (4). The fact that the premium does not disappear entirely in the broader sample (as it did for Ant-specific loans) is expected. While the Sesame Credit Score is a widely used metric, different online platforms utilize proprietary risk assessment models. Nevertheless, the substantial reduction in the coefficient confirms that the relative ease with which women obtain online credit is largely explained by their superior digital credit profiles and lower *prior* credit risk.

5.2 The Welfare Consequences of Obtaining Online Loans

MSEs in China face significant survival challenges. Recent estimates suggest that over 50% of such enterprises fail within their first year (Sun et al.,2023). While fintech

lending has been shown to promote financial inclusion and enhancing firm performance (Hau et al., 2024), the specific impact on survival rates—and whether this impact differs by gender—remains an open question.

To evaluate these welfare effects, we merged our survey data with the business transactional cash flow data from Ant Group. We focus on two primary dependent variables: Survival (a binary indicator of whether the MSEs had business income one-year post-survey), and Revenue (the log amount of that income). To isolate the financial inclusion effect, we restricted the sample to a subsample of 9,067 MSEs that applied for offline loans but were denied. These firms represent a segment with clear financing needs that traditional banks failed to meet.

Columns (1) and (3) of Table 10 present the impact of obtaining an online loan on these outcomes. The results indicate that securing an online loan increases an MSE's survival probability by 3.3% after one year and boosts operating income by 31%. These effects are both statistically significant and economically substantial. The aggregate impact on the Chinese labor market is particularly striking. Based on our estimation, the 3.3 percentage increase in survival rate supported translates to approximately 10.05 million jobs secured annually.[16] This figure represents roughly 1.39% of China's total workforce (734.39 million in 2024).

In Columns (2) and (4), we include an interaction term between Female and Grant (online) to test for gender heterogeneities in these welfare gains. The coefficients for the interaction terms are statistically insignificant, suggesting that the marginal benefits of credit access are similar for both male and female entrepreneurs. While there is no gender-based difference on the intensive margin in terms of survival rate and revenue resulted from loans, the female premium we documented earlier represents a major advantage on the extensive margin (the likelihood of receiving a loan at all). By providing "second-chance" financing to women rejected by traditional banks, online

[16] The total number of secured jobs is calculated as: survival rate increase* portion of MSEs with online loans * (Average employee + 1 entrepreneur) * estimated total MSEs in China. This calculation is: 3.3%*0.821*(6.132+1) *52 million ≈ 10.05 million. The estimates for total MSEs (52 million) is sourced from the State Council Information Office News Release (2023). See http://english.scio.gov.cn/pressroom/2023-03/02/content_85139011.htm.

platforms play a disproportionate role in sustaining female-led entrepreneurship.

[Table 10 about here]

6. Conclusion

By analyzing comprehensive survey data of MSEs in China over 12 consecutive quarters, matched with real business data in China, this study provides robust evidence that digital finance mitigates traditional gender gaps in credit access. We find that female entrepreneurs, on average, possess superior digital creditworthiness. Consequently, they are more likely to access online loans and benefit from lower interest rates compared to their male counterparts. Notably, this “female premium” is most pronounced among long-tail entrepreneurs, those who have been rejected by traditional offline financial institutions. In contrast, we find no significant gender differences in accessing traditional offline loans.

Our mechanism analysis reveals that digital creditworthiness, as proxied by the Sesame Credit Score, accounts for the entirety of the female premium in Ant Group loans and approximately half of the premium across all online lending institutions. This suggests that fintech platforms are successfully "decoding" the latent credit strengths of women through their digital footprints. These online loans provide a critical "second chance" that boosts the survival rate and operating income of small businesses. Based on tracking after-loan performance, entrepreneurs who secured online credit saw a 3.3 percentage point increase in their survival rate and a 31% rise in operating income after one year. Aggregated nationally, the survival gain attributed to online credit translates to securing approximately 1.39% of China’s total workforce. Our findings offer critical policy implications for financial inclusion, particularly in developing countries. While female entrepreneurs have historically faced systemic barriers in conventional credit markets, the rise of fintech offers a significant opportunity for them to bypass the obstacles. By serving long-tail female entrepreneurs overlooked by traditional financial institutions, fintech can capitalize on women’s inherent strengths as reflected in their digital footprints. As demonstrated in the Chinese context, fostering a robust digital

finance ecosystem can generate significant positive welfare effects and drive inclusive economic growth.

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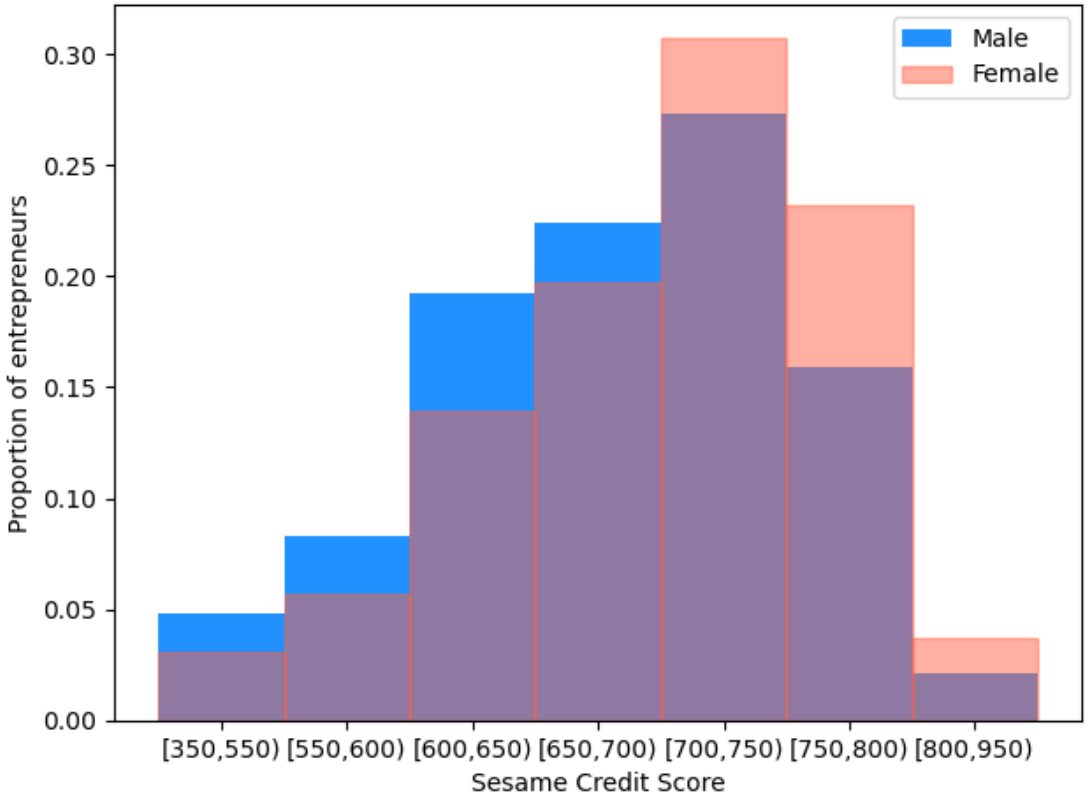
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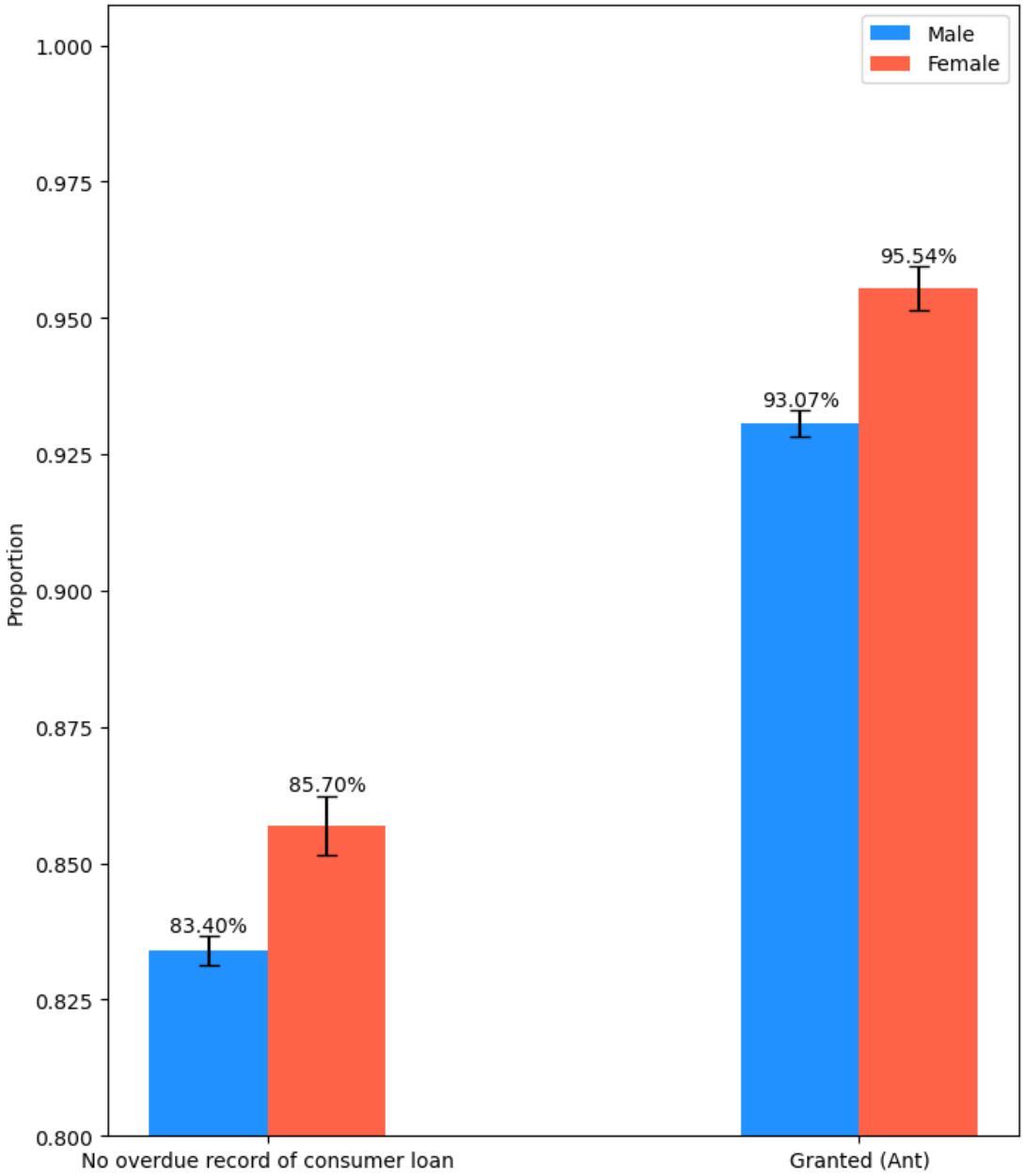
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Figure 1. The distribution of sesame credit scores of entrepreneurs



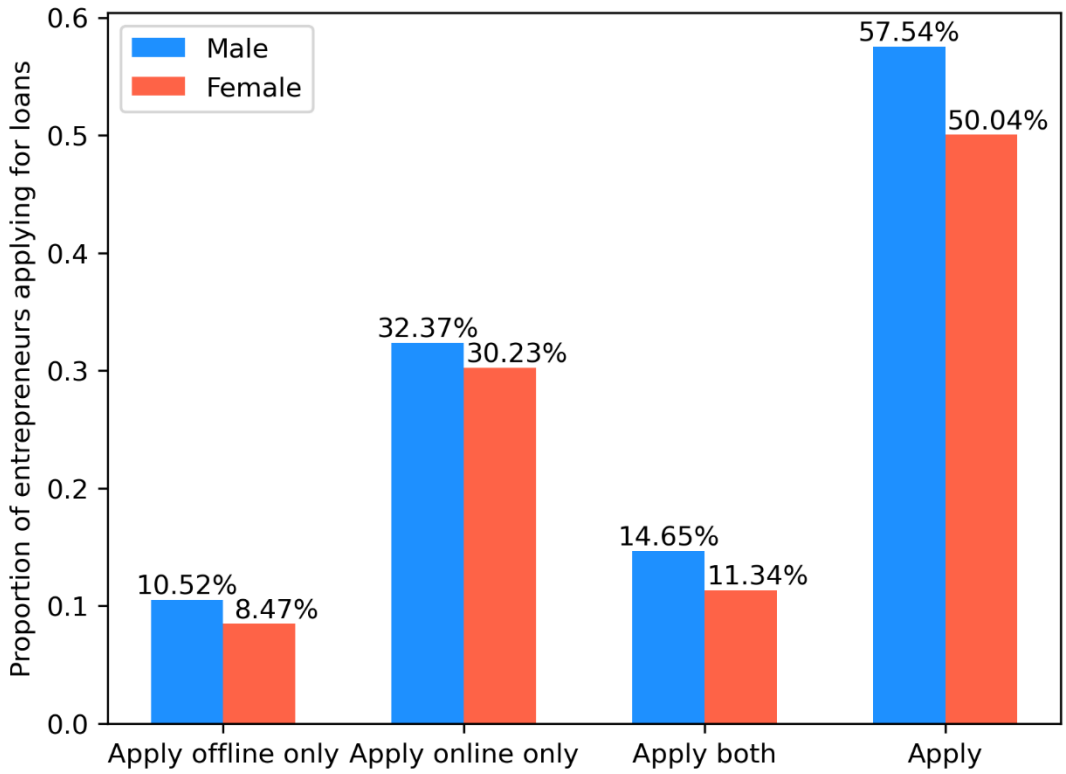
Note: Figure 1 illustrates the distribution of Sesame Credit Scores of male and female entrepreneurs. The Sesame Credit Scores range from 350 to 950 points. The higher the score, the higher creditworthiness. A score between 350 and 550 is considered poor, 550 to 600 moderate, 650 to 700 good, and 700 to 950 excellent.

Figure 2. On-time repayment rate for consumer loans and approval rates of business loans issued by Ant Group



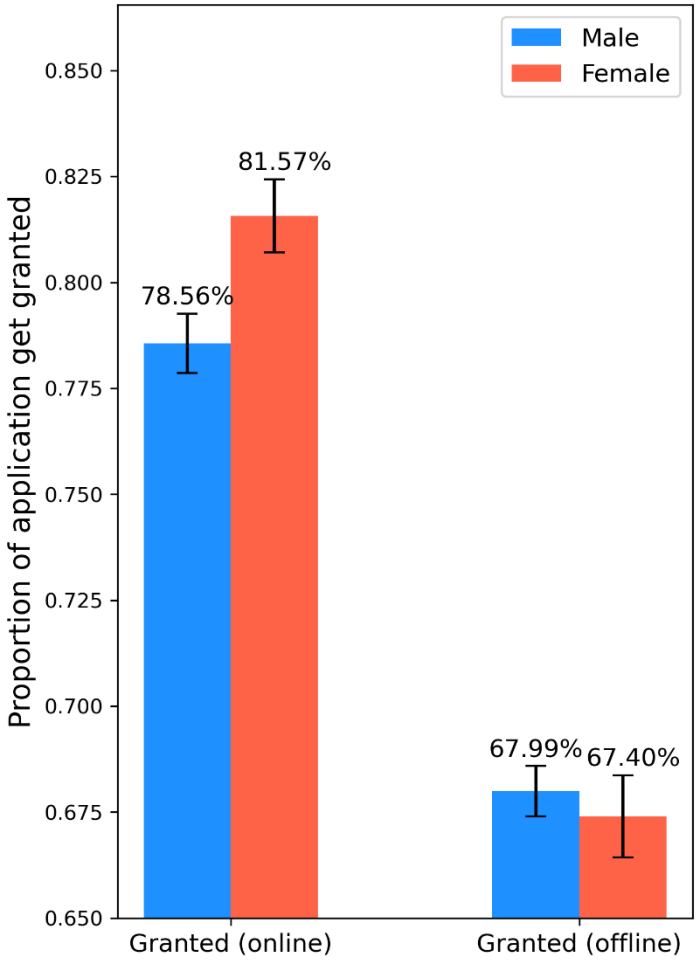
Note: Figure 2 shows the on-time repayment rates for consumer loans and the approval rates for business loans issued by Ant Group, disaggregated by gender. This analysis utilizes a subsample successfully matched with Ant Group's internal records for both consumer and business lending. The whiskers denote the 95% confidence intervals.

Figure 3. Proportions of female and male entrepreneurs applying for online versus offline loans



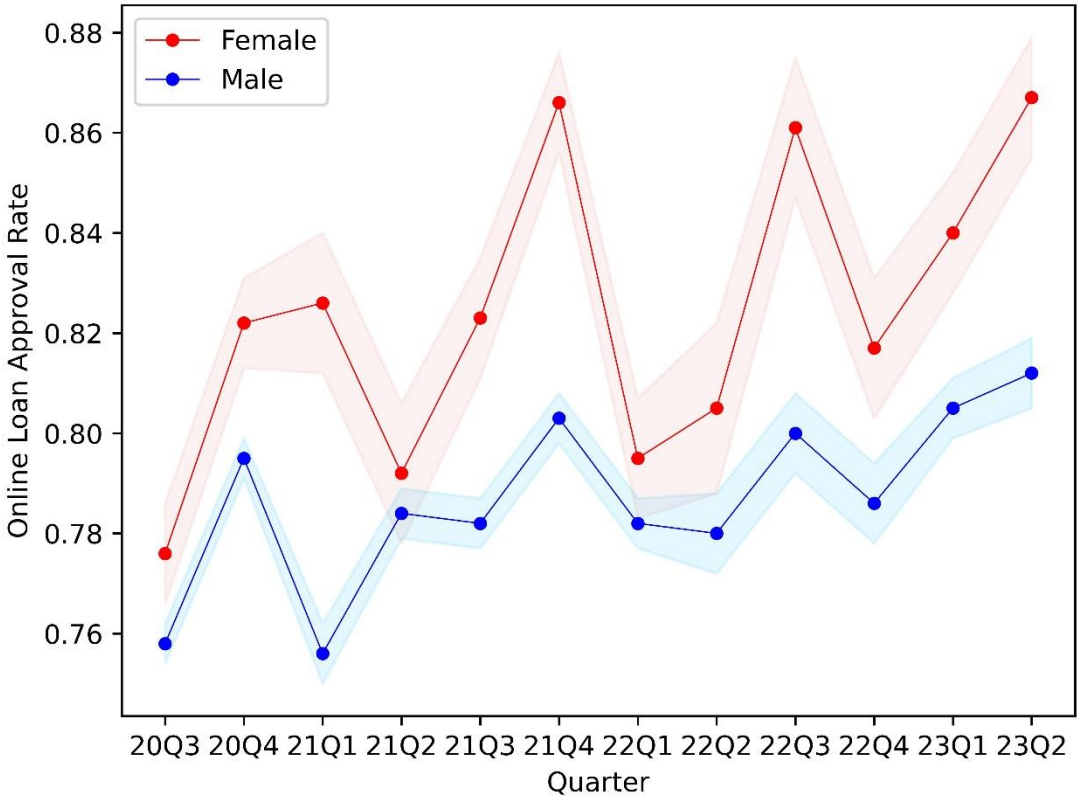
Note: Figure 3 illustrates the proportion of female and male micro and small entrepreneurs who applied for online and offline loans. The final group "Apply" is the union of the preceding three groups, indicating the share of entrepreneurs who applied for at least one type of credit.

Figure 4. Loan approval rates for online and offline loans by gender



Note: Figure 4 illustrates the loan approval probabilities by gender across online and offline channels. The red and blue represent the mean approval rates for female and male entrepreneurs, respectively. Whiskers in the graph indicate the 95% confidence intervals for the statistics.

Figure 5: Quarterly online loan approval rate by gender



Note: Figure 5 illustrates the quarterly online loan approval probabilities for female and male entrepreneurs over 12 consecutive quarters. The red and blue lines represent the approval trends for women and men, respectively, with light shaded regions denoting 95% confidence intervals.

Figure 6. Annual percentage rates (APR) for online and offline loans by gender

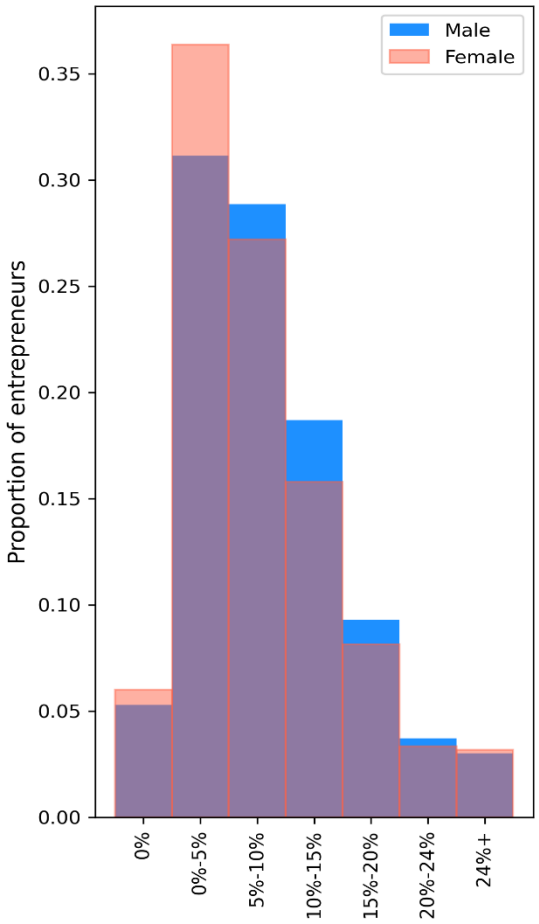


Figure 6a. APR for micro and small entrepreneurs through **online** channels

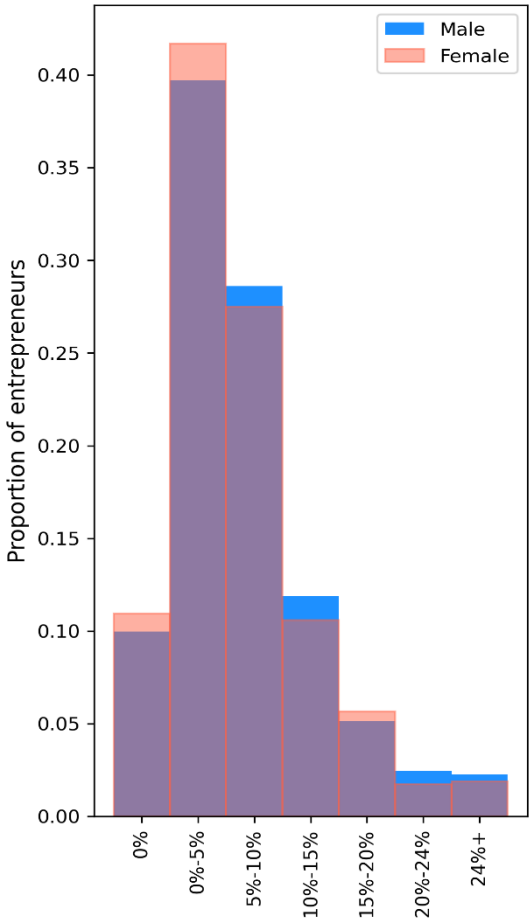


Figure 6b. APR for micro and small entrepreneurs through **offline** channels

Note: Figure 6 illustrates the annual percentage rates (APR) for online or offline loans, disaggregated by gender. Figure 6a displays the distribution of APRs for online loans, while Figure 6b presents the corresponding distribution for offline loans.

Table 1. Sample Construction

Sample	N	Composition	Corresponding dependent variable
Basic groups:	131,106		
Did not apply	56,960		
Apply (online only)	42,108		Granted
Apply (offline only)	13,402		Granted
Apply (both)	18,636		Granted (online), Granted (offline)
Composite samples:			
Apply (online)	60,744	Apply (online only) + Apply (both)	Granted (online)
Apply (offline)	32,038	Apply (offline only) + Apply (both)	Granted (offline)
Apply	74,146	Apply (online only) + Apply (offline only) + Apply (both)	Granted
Apply (online only or offline only)	55,510	Apply (online only) + Apply (offline only)	Granted

Note: This table outlines the construction of the samples used in our study.
We define three subsamples based on survey responses: Apply (online only), Apply (offline only), and Apply (both). From these, we derive four composite samples: (i) Apply (online), comprising those who sought online credit (online only + both); (ii) Apply (offline), comprising those who sought offline credit (offline only + both); (iii) Apply (any), encompassing all applicants; and (iv) Apply (online or offline only), restricted to single-channel applicants. We employ channel-specific binary dependent variables for these samples: Granted (online), Granted (offline), and Granted, each equaling to one if the enterprise successfully secured a loan in that category during the quarter, and zero otherwise.

Table 2. Summary Statistics

Panel A: Key Variables

Variable	N	Mean	SD	Min	Median	Max	Source
Apply (online)	131,106	0.463	0.495	0	1	1	OSOME
Apply (offline)	131,106	0.244	0.429	0	0	1	OSOME
Granted	92,279	0.887	0.315	0	1	1	OSOME
Granted (online)	64,458	0.821	0.383	0	1	1	OSOME
Granted (offline)	33,885	0.705	0.455	0	1	1	OSOME
Granted (Ant)	103,387	0.936	0.228	0	1	1	Ant Group
Loan rate (online)	53,697	8.198	6.363	0	7.5	24	OSOME
Loan rate (offline)	26,349	6.554	5.835	0	4.5	24	OSOME
Loan rate (online or offline only)	48,632	7.572	6.272	0	7.5	24	OSOME
Sesame Credit Score	103,387	4.204	1.421	0	4	7	Ant Group
Survival (after 1 year)	9,067	0.509	0.499	0	1	1	Ant Group
Revenue (after 1 year)	9,067	3.773	4.045	0	1.609	14.461	Ant Group
Female	131,106	0.182	0.386	0	0	1	OSOME
Revenue	131,106	11.535	12.283	0	9.839	14.038	OSOME
Profit margin	131,106	0.018	0.124	-0.2	0	0.2	OSOME
Cash holdings	131,106	2.605	2.081	0	2	6	OSOME
Online sales	131,106	0.156	0.230	0	0.125	0.875	OSOME
Employee	131,106	6.338	25.818	0	2	75	OSOME
Firm age	131,106	4.805	4.919	0	3	23	OSOME
Age	131,106	32.762	9.434	18	32	89	OSOME
Education	131,106	5.309	1.198	1	5	9	OSOME
Child	39,640	0.792	0.774	0	1	2	OSOME (20Q3-20Q4)

Panel B: Female vs. Male

	Female			Male			
Variable	N	Mean	SD	N	Mean	SD	Diff
Apply (online)	23,911	0.416	0.493	107,195	0.470	0.499	-0.054***
Apply (offline)	23,911	0.198	0.400	107,195	0.252	0.435	-0.054***
Granted	12,110	0.881	0.323	62,036	0.869	0.336	0.012**
Granted (online)	10,063	0.816	0.363	50,681	0.786	0.386	0.030***
Granted (offline)	4,805	0.674	0.454	27,233	0.680	0.455	-0.006
Granted (Ant)	18,179	0.955	0.207	85,208	0.931	0.253	0.024***
Loan rate (online)	9,060	7.805	6.341	44,637	8.278	6.365	-0.473***
Loan rate (offline)	3,936	6.541	5.695	22,413	6.610	5.858	-0.069
Loan rate (online or offline only)	8,256	7.335	6.268	40,346	7.620	6.272	-0.285***
Sesame Credit Score	18,179	4.501	1.381	85,208	4.140	1.420	0.361***
Survival (after 1 year)	1,316	0.496	0.500	7,751	0.512	0.499	-0.016
Revenue (after 1 year)	1,316	3.777	4.126	7,751	3.772	4.031	0.005
Revenue	23,911	8.055	19.207	107,195	12.589	25.483	-4.534***
Profit margin	23,911	0.008	0.119	107,195	0.021	0.124	-0.013***
Cash holdings	23,911	2.343	2.031	107,195	2.664	2.087	-0.321***
Online sales	23,911	0.162	0.241	107,195	0.154	0.228	0.008***
Employee	23,911	4.266	19.564	107,195	6.800	26.995	-2.534***
Firm age	23,911	4.793	4.890	107,195	4.807	4.926	-0.014
Age	23,911	35.830	10.365	107,195	32.077	9.074	3.853***
Education	23,911	5.427	1.272	107,195	5.283	1.179	0.144**
Child	7,150	0.908	0.753	32,490	0.767	0.776	0.141***

Note: This table reports the summary statistics for the variables used in our analysis, including the mean, standard deviation, minimum, median, and maximum values. Note that the variables Survival (after 1 year) and Revenue (after 1 year) are restricted to a specific subsample of entrepreneurs who applied for offline loans but were denied, and whose records were successfully matched with Ant Group's longitudinal business data. Consequently, the number of observations for these outcome variables is smaller than for the full sample. Detailed definitions for all other variables are provided in Appendix Table A1.

Table 3. Gender Differences in Online and Offline Loan Applications

	(1)	(2)
Sample:	Full sample	
Dependent variable:	Apply (online)	Apply (offline)
Female	-0.161***	-0.245***
	(0.009)	(0.006)
Revenue	0.246***	0.192***
	(0.019)	(0.014)
Profit margin	-0.817***	-2.291***
	(0.061)	(0.079)
Cash holdings	-0.061***	-0.034***
	(0.003)	(0.002)
Online sales	0.394***	0.151***
	(0.049)	(0.045)
Employee	-0.001***	0.003***
	(0.0002)	(0.0003)
Firm age	-0.020***	-0.005*
	(0.001)	(0.003)
Age	-0.006***	-0.009***
	(0.001)	(0.0004)
Education	0.049***	0.001
	(0.005)	(0.014)
Quarter×Industry FE	Yes	Yes
Province FE	Yes	Yes
Obs.	131,106	131,106
Pseudo R^2	0.022	0.023

Note: This table reports the Logit regression estimates for the probability of loan application by gender. The analysis in Columns (1) and (2) is based on the OSOME dataset, restricted to observations with complete data for all covariates. Full variable definitions are provided in Appendix Table A1. Robust standard errors, clustered at the industry level, are reported in parentheses. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4. Gender Differences in Online and Offline Loan Approvals

	(1)	(2)	(3)	(4)	(5)
Sample:	Apply (online only)	Apply (offline only)	Apply (online only or offline only)	Apply (both)	
Dependent variable:		Granted		Granted (online)	Granted (offline)
Female	0.135***	0.020	-0.017	0.219***	0.065
	(0.036)	(0.057)	(0.071)	(0.054)	(0.064)
Female×Apply (online only)			0.147*		
			(0.081)		
Apply (online only)			0.028		
			(0.032)		
Revenue	0.031**	0.057***	0.024**	0.081***	0.102***
	(0.012)	(0.018)	(0.012)	(0.020)	(0.020)
Profit margin	0.998***	-0.092	0.349***	1.021***	1.244***
	(0.116)	(0.179)	(0.113)	(0.275)	(0.195)
Cash holdings	0.056***	0.002	0.066***	0.098***	0.084***
	(0.007)	(0.010)	(0.007)	(0.014)	(0.017)
Online sales	0.158**	-0.276***	0.308***	0.283***	-0.105
	(0.061)	(0.101)	(0.062)	(0.086)	(0.065)
Employee	-0.003***	0.001	0.000	-0.0012***	-0.0004
	(0.001)	(0.001)	(0.001)	(0.0004)	(0.001)
Firm age	0.035***	0.025***	0.032***	0.031***	0.025**
	(0.004)	(0.005)	(0.003)	(0.004)	(0.011)
Age	0.012***	-0.001	-0.000	0.007***	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Education	0.115***	-0.017	0.084***	0.057***	0.016
	(0.012)	(0.014)	(0.010)	(0.015)	(0.016)
Quarter×Industry FE	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
Obs.	42,108	13,402	55,510	18,636	18,636
Pseudo R^2	0.017	0.004	0.010	0.033	0.030

Note: This reports Logit regression estimates for the probability of loan approval. Columns (1) and (2) analyze enterprises that applied exclusively for online or offline loans, respectively. Column (3) pools these two subsamples. Columns (4) and (5) focus on enterprises that sought credit through both channels simultaneously. The dependent variables are binary indicators: Granted equals one if any loan was secured; Granted (online) and Granted (offline) are specific to the respective lending channels. All models include controls as defined in Appendix Table A1. Robust standard errors clustered at the industry level are reported in parentheses. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5. Gender and Loan Origination: A Heckman Two-Stage Analysis

Panel A: Stage one

	(1)	(2)	(3)
Dependent variable:	Apply (online)	Apply (offline)	Apply (both)
Female	-0.037**	-0.108***	-0.065***
	(0.017)	(0.018)	(0.021)
Revenue	0.122***	0.112***	0.132***
	(0.006)	(0.006)	(0.007)
Profit	-0.383***	-1.460***	-1.001***
	(0.057)	(0.061)	(0.069)
Cash holdings	-0.037***	-0.019***	0.025***
	(0.003)	(0.003)	(0.004)
Online sales	0.361***	0.143***	0.247***
	(0.029)	(0.031)	(0.034)
Employee	-0.001***	0.002***	0.001***
	(0.0002)	(0.0002)	(0.0003)
Firm age	-0.019***	-0.003**	-0.006***
	(0.001)	(0.0016)	(0.002)
Age	-0.004***	-0.006***	0.003***
	(0.001)	(0.001)	(0.001)
Education	0.038***	-0.008*	0.032***
	(0.005)	(0.005)	(0.006)
Child	0.093***	0.089***	0.110***
	(0.009)	(0.010)	(0.011)
Quarter×Industry FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Obs.	39,640	39,640	39,640
Pseudo R^2	0.026	0.030	0.029

Panel B: Stage two

	(1)	(2)	(3)	(4)
Sample:	Apply (online)	Apply (offline)	Apply (both)	
Dependent variable:	Granted (online)	Granted (offline)	Granted (online)	Granted (offline)
Female	0.141***	0.129	0.274***	-0.034
	(0.002)	(0.085)	(0.053)	(0.047)
IMR	-2.527***	-0.802***	-1.785***	-1.151***
	(0.003)	(0.689)	(0.315)	(0.292)
Controls	Yes	Yes	Yes	Yes
Quarter×Industry FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Obs.	18,644	10,434	6,191	6,191
Pseudo R^2	0.029	0.018	0.046	0.035

Note: The table uses the Heckman two-stage method to estimate the effect of gender on loan approval while accounting for selection bias. The sample is restricted to 39,640 observations from 20Q3 and 20Q4, as these quarters include data on the number of children, which serves as our exclusion restriction. Panel A reports the first-stage selection equation, where 'Child' (the number of children in the household) is used to identify the model. Panel B presents the second-stage results, incorporating the Inverse Mills Ratio (IMR) to correct for selection. Specifically, the IMR in Panel B, Columns (1) and (2), is derived from the corresponding columns in Panel A, while the IMR for Columns (3) and (4) is calculated from Panel A, Column (3). Estimates are produced using a Logit model, and full variable definitions are available in Appendix Table A1. Robust standard errors clustered at the industry level are reported in parentheses. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 6. Online Loan Approval Probabilities by Gender, Conditional on Offline Credit Outcomes

	(1)	(2)
	Apply (both) & Granted (offline)=1	Apply (both) & Granted (offline)=0
Dependent variable:	Granted (online)	
Female	0.074	0.293***
	(0.051)	(0.071)
Controls	Yes	Yes
Quarter×Industry FE	Yes	Yes
Province FE	Yes	Yes
Obs.	12,575	6,057
Pseudo R^2	0.038	0.034
Avg. granted (online) rate	89.1%	57.9%

Note: This table examines the relationship between the gender of the entrepreneur and the probability of online loan approval, conditioned on their offline loan status. Columns (1) and (2) report results for subsamples of enterprises that were granted or denied offline loans, respectively. Estimates are derived using a Logit model, and detailed variable definitions are provided in Appendix Table A1. Robust standard errors clustered at the industry level are in parentheses. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 7. Gender and Business Operation among Online Loan Recipients

	(1)	(2)	(3)
Sample:		Granted (online)=1	
Dependent variable:	Revenue	Profit margin	Cash holdings
Female	-0.282***	-0.013***	-0.263***
	(0.024)	(0.001)	(0.031)
Online sales	0.679***	0.080***	1.018***
	(0.032)	(0.004)	(0.059)
Employee	0.009***	0.001***	0.006***
	(0.001)	(0.0002)	(0.0004)
Firm age	0.037***	0.002**	0.030***
	(0.003)	(0.0002)	(0.003)
Age	0.018***	0.0005***	-0.005**
	(0.001)	(0.0001)	(0.002)
Education	0.061***	-0.002***	0.013**
	(0.005)	(0.0003)	(0.006)
Quarter×Industry FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Obs.	58,153	58,153	58,153
Adj R^2	0.125	0.046	0.040

Note: This table examines the relationship between an entrepreneur's gender and firm performance among businesses that secured online credit. The analysis focuses on three key outcomes: Revenue (quarterly operating income), Profit Margin, and Cash Holdings, the latter defined as the number of months current cash flow can sustain operations. Estimates are produced using an OLS model Full variable definitions are provided in Appendix Table A1. Robust standard errors, clustered at the industry level, are reported in parentheses. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 8. Gender Differences in Loan Interest Rates across Lending Channels

	(1)	(2)	(3)	(4)	(5)
Sample:	Granted (online only)	Granted (offline only)	Granted (online or offline only)	Granted (both)	
Dependent variable:	Loan rate (online)	Loan rate (offline)	Loan rate (online or offline only)	Loan rate (online)	Loan rate (offline)
Female	-0.575***	0.026	-0.224	-0.453***	-0.175
	(0.122)	(0.100)	(0.163)	(0.126)	(0.141)
Female×Granted (online only)			-0.299*		
			(0.180)		
Grant (online only)			2.917***		
			(0.072)		
Revenue	0.399***	0.524***	0.436***	0.238***	0.102**
	(0.037)	(0.057)	(0.024)	(0.033)	(0.045)
Profit margin	-1.425***	-1.342***	-1.410***	-3.286***	-3.045***
	(0.342)	(0.369)	(0.242)	(0.421)	(0.499)
Cash holdings	-0.249***	-0.025	-0.197***	-0.172***	-0.154***
	(0.026)	(0.028)	(0.014)	(0.041)	(0.041)
Online sales	0.290	1.582***	0.552***	1.872***	2.327***
	(0.270)	(0.472)	(0.123)	(0.494)	(0.410)
Employee	-0.004*	0.006***	0.001	0.016***	0.016***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)
Firm age	0.019**	0.004	0.015**	0.029*	0.033**
	(0.007)	(0.012)	(0.006)	(0.015)	(0.012)
Age	0.034***	-0.001	0.025***	0.007	0.001
	(0.005)	(0.006)	(0.003)	(0.007)	(0.007)
Education	0.392***	0.209***	0.322***	0.172*	0.076
	(0.089)	(0.051)	(0.025)	(0.071)	(0.079)
Granted amount	0.008***	0.007***	0.007***	0.021***	0.007***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Quarter×Industry FE	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
Obs.	38,707	11,038	49,745	15,263	15,070
Adj R^2	0.028	0.053	0.063	0.047	0.047

Note: This table examines the relationship between an entrepreneur's gender and the interest rates applied to their loans. Columns (1) and (2) focus on single-channel borrowers who received credit exclusively through online or offline channels, respectively. Column (3) pools these two groups. Columns (4) and (5) analyze dual-channel borrowers who secured both online and offline loans during the period. Estimates are derived using an OLS model. Full variable definitions of the variables are provided in Appendix Table A1. Robust standard errors, clustered at the industry level, are reported in parentheses. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 9. The Impact of Sesame Credit Scores and Gender on Loan Approval

	(1)	(2)	(3)	(4)	(5)
Sample:	Matched with Ant record			Apply (both)	
Dependent variable:	Sesame Credit Score	Granted (Ant)	Granted (Ant)	Granted (online)	
Female	0.204***	0.030***	-0.007*	0.027***	0.020***
	(0.019)	(0.005)	(0.004)	(0.008)	(0.007)
Sesame Credit Score			0.182***		0.058***
			(0.003)		(0.003)
Controls	Yes	Yes	Yes	Yes	Yes
Quarter×Industry FE	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
Obs.	103,387	103,387	103,387	13,813	13,813
Adj R^2	0.123	0.081	0.303	0.030	0.055

Note: This table examines the relationship between Sesame Credit Scores, entrepreneur gender, and loan approval outcomes. The analysis in Columns (1) through (3) is based on a subsample of survey respondents successfully matched with their official Ant Group business loan records. Columns (4) and (5) comprise observations of entrepreneurs who sought credit through both online and offline channels (not restricted to Ant Group) within a given quarter. Estimates are derived using an OLS model. Full variable definitions are provided in Appendix Table A1. Robust standard errors, clustered at the industry level, are reported in parentheses. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

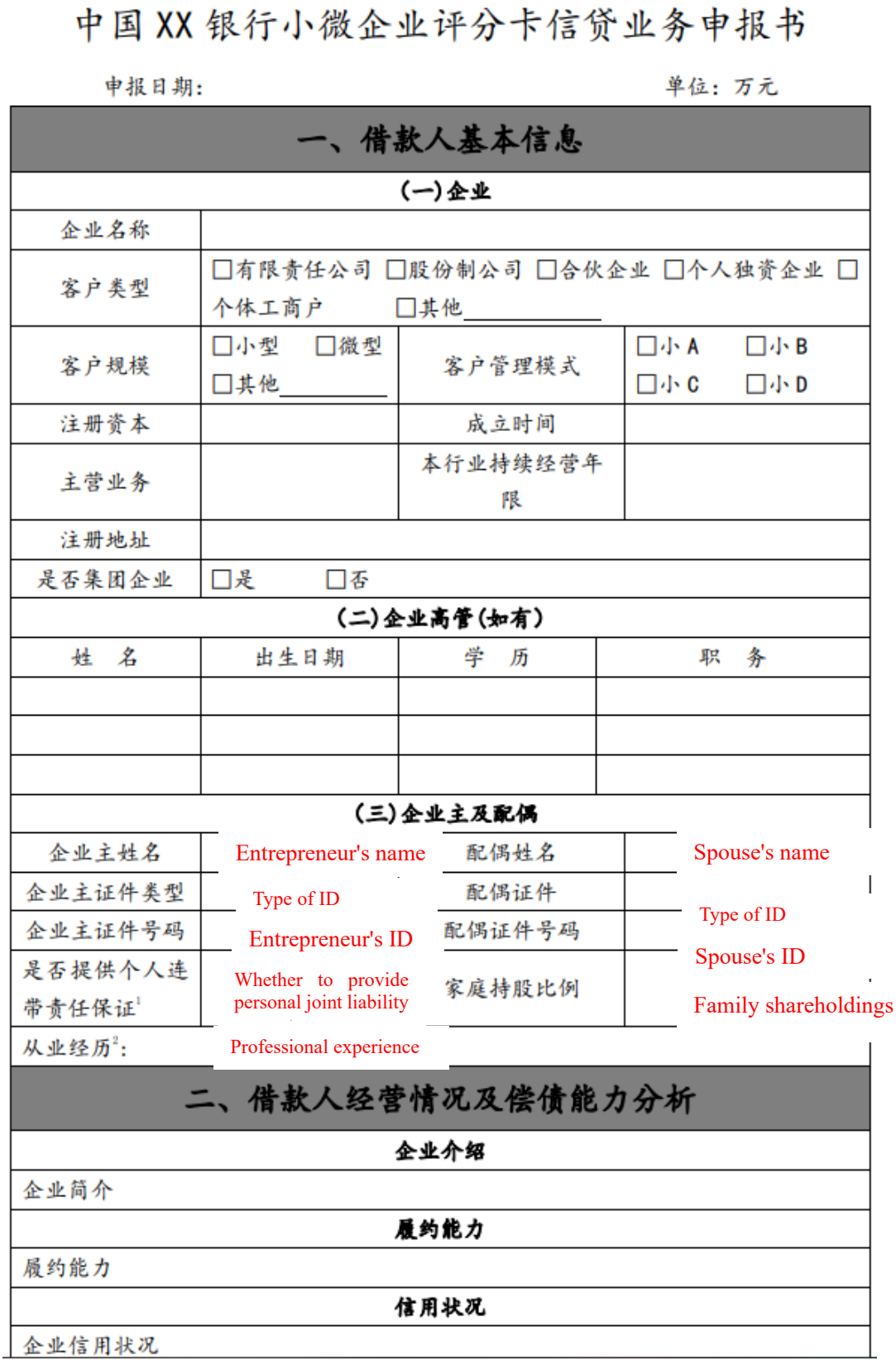
Table 10. The Impact of Digital Inclusion on MSEs' Survival and Revenue: A One-year Post-Loan Analysis

	(1)	(2)	(3)	(4)
Sample:	Apply (offline)=1 & Granted (offline)=0			
Dependent variable:	Survival (after 12 months)		Revenue (after 12 months)	
Granted (Online)	0.033***	0.034***	0.310***	0.312***
	(0.007)	(0.007)	(0.054)	(0.058)
Female		-0.001		0.071
		(0.020)		(0.157)
Female×Granted (Online)		-0.009		-0.0143
		(0.014)		(0.100)
Controls	Yes	Yes	Yes	Yes
Quarter×Industry FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Obs.	9,067	9,067	9,067	9,067
Adj R^2	0.008	0.008	0.015	0.015

Note: This table examines the welfare effects of online financial inclusion by focusing on a subsample of entrepreneurs who were denied offline credit during the quarter. This specific focus on credit-constrained firms results in a reduced sample of 9,067 observations. Estimates are produced using an OLS model. Full variable definitions are provided in Appendix Table A1. Robust standard errors, clustered at the industry level, are reported in parentheses. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Appendix

Figure A1: A bank's micro and small business credit card



中国 XX 银行小微企业评分卡信贷业务申报书

申报日期：　　单位：万元

一、借款人基本信息			
(一)企业			
企业名称			
客户类型	□有限责任公司 □股份制公司 □合伙企业 □个人独资企业 □个体工商户 □其他_____		
客户规模	□小型 □微型 □其他_____	客户管理模式	□小 A □小 B □小 C □小 D
注册资本		成立时间	
主营业务		本行业持续经营年限	
注册地址			
是否集团企业	□是 □否		
(二)企业高管(如有)			
姓　名	出生日期	学　历	职　务
(三)企业主及配偶			
企业主姓名	Entrepreneur's name	配偶姓名	Spouse's name
企业主证件类型	Type of ID	配偶证件	Type of ID
企业主证件号码	Entrepreneur's ID	配偶证件号码	Spouse's ID
是否提供个人连带责任保证[1]	Whether to provide personal joint liability	家庭持股比例	Family shareholdings
从业经历[2]:	Professional experience		
二、借款人经营情况及偿债能力分析			
企业介绍			
企业简介			
履约能力			
履约能力			
信用状况			
企业信用状况			

企业主及配偶信用状况 Entrepreneur and spouse's credit status
其他违约记录（包括工商、环保、海关、司法以及贸易伙伴的违约记录情况）
资产状况
1。企业资产 （1）经营场所：□自有 □长期（3 年以上）租赁 □短期（3 年以内）租赁 □其他 (2)金融资产情况（包括存款、国债、理财产品、贵金属等） 无 （3）其他资产情况(包括房产、土地、厂房、车辆、设备、存货等情况） 无
2. 企业主及配偶资产 Entrepreneur and spouse's property （1）金融资产情况(包括存款、国债、理财产品、贵金属以及建行近 12 个月 AUM 均值等） （2）其他资产情况（包括自有房产、车辆等情况）
环保或其他行业标准达标情况
是否达到环保、卫生、食品安全，或其他行业标准。 是
财务情况

上年度销售收入		上年度利润总额	
主要结算银行		承诺销售归行率	

近 2 年在 xx 银行业务合作情况介绍(其中应重点说明在我行的授信情况)：

Note: This table shows the scorecard of a large domestic bank for assessing the credit risk of MSEs. Elements related to the entrepreneur's personal information have been translated into English and are highlighted in red.

Table A1. Variable Definitions

Variable	Definition
Dependent variables	
Apply (online)	A dummy variable that equals one if an enterprise applies for an online loan in survey quarter, and zero otherwise.
Apply (offline)	A dummy variable that equals one if an enterprise applies for an offline loan in survey quarter, and zero otherwise.
Granted	A dummy variable that equals one if an enterprise's loan application is granted, and zero otherwise.
Granted (online)	A dummy variable that equals one if an enterprise's online loan application is granted, and zero otherwise.
Granted (offline)	A dummy variable that equals one if an enterprise's offline loan application is granted, and zero otherwise.
Loan rate (online)	The annualized interest rate of the online loan.
Loan rate (offline)	The annualized interest rate of the offline loan.
Granted (Ant)	A dummy variable for the credit limit of the respondents at Ant Group by the end of that month. It is assigned a value of 1 if the credit limit is greater than 0, and a value of 0 if the credit limit is equal to 0.
Survival (after 1 year)	The survival status of the respondents on the Alipay platform 12 months later. It is assigned a value of 1 if there is transaction flow, and a value of 0 if there is no transaction flow.
Revenue (after 1 year)	The logarithm of the respondents' business income on the Alipay platform 12 months later.
Independent variable	
Female	A dummy variable that equals one if the entrepreneur is female, and zero if the entrepreneur is male.
Sesame Credit Score	A categorical variable for respondents' Sesame Credit Scores. 1 represents scores in [350, 550), 2 for [550, 600), 3 for [600, 650), 4 for [650, 700), 5 for [700, 750), 6 for [750, 800), and 7 for [800, 950].
Control variables	
Revenue	The natural log of a company's revenue in Chinese yuan.
Profit margin	Business profit margins as reported in percentage.
Cash holdings	Cash holding as reported as the number of months a business can sustain.
Online sales	The percentage of a business's online sales to total sales.
Employee	The natural log of the number of employees in a business.
Firm age	The number of years since the business was founded.
Age	The age of the entrepreneur.
Education	A categorical variable for identifying education level, with "No schooling" coded as 1, "Preschool education" as 2, "Primary school" as 3, "Junior high school" as 4, "Senior high school" as 5, "Junior college (associate degree)" as 6, "Undergraduate (bachelor's degree)" as 7, "Master's degree" as 8, and "Doctoral degree" as 9.
Child	The number of children in the entrepreneur's family.

Table A2. Criteria for Classifying Micro, Small, and Medium-Size Enterprises

Name of industry	Indicators	Micro	Small	Medium size
Agriculture	Revenue (R)	R<50	50<R<500	500<R<20,000
Industrial	Employee (E)	E<20	20<E<300	300<E<1,000
	Revenue (R)	R<300	300<R<2,000	2,000<R<40,000
Construction	Revenue (R)	R<300	300<R<6,000	6,000<R<80,000
	Assets (A)	A<300	300<A<5,000	5,000<A<80,000
Wholesale trade	Employee (E)	E<5	5<E<20	20<E<200
	Revenue (R)	R<1,000	1,000<R<5,000	5,000<R<40,000
Retail	Employee (E)	E<10	10<E<50	50<E<300
	Revenue (R)	R<100	100<R<500	500<R<20,000
Transportation	Employee (E)	E<20	20<E<300	300<E<1,000
	Revenue (R)	R<200	200<R<3,000	3,000<R<30,000
Storage	Employee (E)	E<20	20<E<100	100<E<200
	Revenue (R)	R<100	100<R<1,000	1,000<R<30,000
Postal	Employee (E)	E<20	20<E<300	300<E<1,000
	Revenue (R)	R<100	100<R<2,000	2,000<R<30,000
Accommodation	Employee (E)	E<10	10<E<100	100<E<300
	Revenue (R)	R<100	100<R<2,000	2,000<R<10,000
Catering	Employee (E)	E<10	10<E<100	100<E<300
	Revenue (R)	R<100	100<R<2,000	2,000<R<10,000
Information transmission	Employee (E)	E<10	10<E<100	100<E<2,000
	Revenue (R)	R<100	100<R<2,000	2,000<10,000
Software and IT	Employee (E)	E<10	10<E<100	100<E<300
	Revenue (R)	R<50	50<R<1000	1,000<R<10,000
Real estate development	Revenue (R)	R<100	100<R<1,000	1,000<R<10,000
	Assets (A)	A<2,000	2,000<A<5,000	5,000<A<10,000
Property management	Employee (E)	E<100	100<E<300	300<E<1,000
	Revenue (R)	R<500	500<R<1,000	1,000<R<5,000
Leasing & business services	Employee (E)	E<10	10<E<100	100<E<300
	Assets (A)	A<100	100<A<8,000	8,000<A<120,000
Others	Employee (E)	E<10	10<E<100	100<E<300

Note: In late 2017, the National Bureau of Statistics issued the Measures for the Classification of Statistically Large, Small, Medium and Micro Enterprises (2017), amending the Notice on Issuing the Standard Provisions for the Classification of Small and Medium Enterprises (Ministry of Industry and Information Technology Enterprise [2011] No. 300), jointly issued by the former Ministry of Industry and Information Technology, the National Bureau of Statistics, the National Development and Reform Commission, and the Ministry of Finance. It is used as the basis for defining the sizes of small and medium-size enterprises in the "three not less than" and "two increase and two control" assessment indicators of commercial banks by the China Banking Regulatory Commission. We only list the criteria for classifying micro, small, and medium-size enterprises that are relevant to this paper. The unit of measurement for revenue and assets in this table is RMB ten thousand (10,000 RMB).

Table A3. The Number of Children and Online Business Activities

	(1)	(2)
Dependent variable:	Online sales	
Female	0.021***	0.021***
	(0.002)	(0.001)
Child	-0.016***	-0.016***
	(0.003)	(0.003)
Female×Child		-0.001
		(0.003)
Controls	Yes	Yes
Quarter×Industry FE	Yes	Yes
Province FE	Yes	Yes
Obs.	39,640	39,640
Adj R^2	0.117	0.117

Note: This table examines the relationship between the number of children and the online business activities of entrepreneurs. The sample used is consistent with Panel A of Table 5. Definitions of the variables are provided in Appendix Table A1. Robust standard errors, clustered at the industry level, are reported in parentheses. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.