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Identifying gender disparities on the time to repay microfinance group loans: Evidence from Mexico*

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Abstract: This paper investigates how gender disparities affect the time to repay group micro-finance loans using survival analysis and hazard decomposition techniques. We also control for the effect of the COVID-19 pandemic on the time needed by micro-finance loan borrowers to repay. We use a large sample of bank microfinance group loans from August 2017 to August 2021. Despite the fact that female borrowers' overall default rate is smaller, our unconditional estimates show that female borrowers default almost the equivalent of three consecutive installments earlier. Moreover, this result persists when we control for micro, industry, and macroeconomic factors. We also observe that the COVID-19 pandemic materialized as a spike in aggregate default rates that gradually reduced afterward. Our study identified a potential gender gap that has been understudied in the literature.

Keywords: Credit markets; Microfinance loan; Group lending; Gender; Survival analysis

JEL Classification: C41, G21, J16, O12, O16

Resumen: En este documento se investiga cómo las disparidades de género afectan el tiempo de repago de los microcréditos grupales utilizando técnicas de análisis de supervivencia y de descomposición de la función de riesgo. Además, se controla el efecto que tuvo la pandemia de COVID-19 sobre el tiempo de repago requerido por los acreditados de microcréditos. Se utilizó una muestra grande de microcréditos grupales bancarios de agosto de 2017 a agosto de 2021. A pesar de que la tasa de incumplimiento de las mujeres acreditadas es menor, las estimaciones incondicionales muestran que el incumplimiento de las mujeres acreditadas ocurre antes y es de aproximadamente el equivalente a tres pagos consecutivos. Más importante aún, este resultado persiste cuando se controla por factores micro, industriales y macroeconómicos. También, se observa que la pandemia por COVID-19 se materializó como un pico en las tasas de incumplimiento agregadas que posteriormente se redujo gradualmente. El estudio identificó una brecha de género potencial que ha sido poco estudiada en la literatura.

Palabras Clave: Mercados de crédito; Microcréditos; Microcréditos grupales; Género; Análisis de supervivencia

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1. Introduction

A vast body of the microfinance literature has investigated and documented the role of gender in determining the likelihood of loan repayment. Research documenting the association between gender and microfinance loan repayment reports mixed results. On the one hand, a number of studies report that women perform better in some dimensions of loan repayment (Chakravarty et al., 2013; Shariar et al., 2020). On the other hand, according to some studies, there is no statistically significant relationship between gender and loan repayment when other variables are considered (Bhatt and Tang, 2002; Dorfleitner et al., 2017). Surprisingly, none of these studies have investigated the issue of the link between gender and the time when default occurs.

In this paper, we use unique loan-level data on microfinance borrowers for group loans to investigate if there is evidence of gender bias in the time to loan default during the period from August 2017 to August 2021 in Mexico. Specifically, we use unconditional and conditional survival analysis to assess how gender and its interactions with other factors determine the loan's time to default performance. We also assess how the COVID-19 pandemic affected default dynamics in the Mexican microfinance banking sector. Finally, we use a hazard decomposition technique based on aggregate data and decompose the gender gap in default rates into a characteristics (or endowments) component and a coefficient (or effects) component. This paper is an attempt to measure the presence of strategic default behavior using unconditional and conditional differences in the loan's median time to repay by gender.

Analyzing the determinants of the time to default from the perspective of gender is relevant for the following two reasons. First, there is a possibility that female obligors tend to default earlier due to a strategic behavior as envisaged theoretically by Ho and Mallick (2017) for loans granted by microfinance institutions (MFIs). A comprehensive understanding of the size and determinants of gender disparities in time to repay microfinance loans may assist policymakers in developing policy measures to promote female financial inclusion. Second, an obligor that defaults earlier may pose a higher credit risk for the financial intermediary. MFIs may enhance the current internal credit risk methodologies to mitigate solvency risks and refine pricing models to offer improved

products for women. Gains in pricing efficiency and risk management practices of MFIs boost competition in the sector, and this usually leads to benefits in terms of more favorable credit conditions for the borrowers.

Our paper is motivated by the theoretical model of Ho and Mallick (2017) that describes the origin of strategic default behavior toward bank loans among microfinance borrowers. The model assumes that there is an asymmetry of information between the commercial bank and a rural borrower who requires funds to invest in a project. Conditional on a positive decision by the bank to grant the loan, the borrower faces a trade-off between an expected payoff of repaying the loan and the benefit of shirking, which is equal to the loan amount. The return of the project depends on the borrower's effort and marginal cost, which is stochastic and unobservable. Strategic default occurs when the obligor receives the loan and deliberately makes no or insufficient effort to repay it. In this model, the borrower's effort determines the occurrence and timing of default.

According to Ho and Mallick (2017), the probability of strategic default depends on three factors: i) the probability that the obligor puts the maximum effort into the project used to repay the loan, ii) the value and distribution of the marginal effort cost of the borrower, and iii) the probability of bank's belief that the borrower will put in full effort. These three input variables may lead to an earlier (later) group default and a greater (lower) number of group defaults by gender.

Other studies in the literature have suggested that strategic default may arise as a consequence of health shocks (e.g., accident, fracture, operation, non-communicable disease; see Hossain et al., 2019); support or burden of relatives (Al-Azzam et al., 2020); socioeconomic factors (Abimbola, 2021); poverty (Zainuddin and Yassin, 2019); religion, technological, screening, and monitoring variables (Hill and Sarangi, 2012); innate trustworthiness (Shahriar et al., 2020); member social ties and quality of the group leaders (Al-Azzam et al., 2013); institutional context (Boehe and Cruz, 2013); social capital variables such as geographical proximity, trust, friendship, group homogeneity, and acquaintanceship (Al-Azzam et al., 2020); and exposure to physical or sexual violence among married women (Shahriar, 2016). Most of these studies focus on the overall default determinants, and none of them use survival analysis or hazard decomposition analysis to

investigate the association of gender on the time to repay group loans. In other words, the analysis of the time to default remains understudied in the existing literature.

We report that the overall steady state (i.e., full sample) default rate is lower for women borrowers. This result suggests that female borrowers present lower credit risk. Interestingly, our novel finding is that according to female unconditional and conditional median survival time estimates for group loans, female borrowers default earlier compared with men borrowers. In fact, the difference in the conditional median time to default by gender is statistically significant at the 1 percent level even when we control for loan and borrowers' characteristics, as well as industry and macroeconomic variables. Thus, in contrast to the previous research, our result suggests that female borrowers present greater credit risk in terms of default time. The overall impact on credit risk is undetermined as it depends on the time value of the size of the economic loss by gender and the composition of the loan portfolio of MFIs. Further, we observe that this difference by gender in terms of time to default persists in the presence of the COVID-19 health shock.

Our analysis further shows that an increase in the past aggregate loan default rate, real interest rate, and group size is associated with an increase in credit risk. In contrast, an increase in the loan's term to maturity, loan size, borrower's age, and foreign remittances is associated with a decrease in credit risk. We also find that female borrowers and single individuals are associated with greater credit risk, whereas restructured loans have lower credit risk. This suggests that younger and single female borrowers are more likely to commit an earlier group loan default. This result is congruent with the idea that single and young women default earlier because the probability of them putting in their maximum effort into the project is lower since the benefit of accessing future financing is not enough to compensate for the saving in costs on doing nothing (Ho and Mallick, 2017). The hazard decomposition analysis based on the difference in the aggregate crude default rate between female and male obligors suggests that the characteristics component is the most relevant in explaining the gender gap.

The rest of the paper is organized as follows. In Section 2, we summarize the literature review. In Section 3, we present our loan default definitions along with the characteristics of our data, variable selection criteria, and methodology. In Section 4, we

report the results of our multivariate analysis, including our main findings. Finally, in Section 5, we present the conclusions of our analyses and policy recommendations.

2. Related existing studies

This paper is related to three lines of research pertaining to loan repayment.¹ The first is research about the impact of gender disparities on microfinance loan repayment. The evidence presented by this literature can be classified in terms of both scope and data type (e.g., global or aggregate data at the entity level and single country or granular product-specific data).² A few papers that have used global data report that women are better borrowers as a higher percentage of female clients in MFIs is associated with lower portfolio at risk, fewer write-offs, and fewer provisions (D'espallier et al., 2011; Zainuddin and Yasin, 2019). Naturally, country characteristics such as the pace of economic growth and the degree of financial sector development and deepness affect the performance of MFIs. Ahlin et al. (2011) show that countries with more developed financial sectors exhibit lower default rates in microcredits. Also, there is mixed evidence for a number of papers that study this issue at the country level. On the one hand, a number of studies report that women have a better performance in terms of loan repayment.³ On the other hand, there are also studies suggesting that there is no statistically significant relationship between gender and loan repayment when other variables are considered.⁴ Our study is similar in nature to research focusing on identifying the determinants of loan delinquency (Azzam et al., 2020), which does not necessarily imply loan default. Both global and domestic studies focus on repayment, and neither of them analyzes gender disparities related to the time to default.

Second, the contributions of our paper are similar to that of the studies of credit risk based on reduced-form models⁵ using survival analysis,⁶ which have been widely used to

¹ Banerjee (2013) provides an excellent review on microcredit.

² Cross-country studies suffer from a lack of granularity as data from individual loans or products are not publicly available to preserve domestic banking rules related to individual obligors' data sharing.

³ For example, Shariar et al. (2020) and Chakravarty et al. (2013) study a loan sample in Bangladesh; Kevane and Wydick (2001) study a loan sample in Guatemala; Medina-Olivares et al. (2021) study a Chinese microfinance individual and group loan sample.

⁴ For instance, Bhatt and Tang (2002) study a sample of microfinance institutions in the United States; Dorfleitner et al. (2017) analyze a sample of agricultural loans in Guatemala.

⁵ Reduced form models started with the early studies of Altman (1968) and Ohlson (1980).

assess the determinants of the time to default of different loan types: Glennon and Nigro (2005) for a sample of small and medium-sized U.S. firms, Dirick et al. (2017) for a sample of European firms, Andreeva (2006) and Bellotti and Crook (2009) for a sample of European and UK revolving credit cards, and Goedecke (2018) for a sample of Mexican microfinance group loans.⁷ Our paper is the first to analyze in great depth the link between gender disparities and its interactions with the time to repay for group microfinance borrowers.

Third, we link our work to research on the impact of the COVID-19 pandemic on micro-loan repayment and gender-gap access (Agarwal, 2021; Hewa-Wellalage et al., 2022). COVID-19 was a global public health crisis that imposed multiple challenges to economic development and affected gender equality. A number of factors exerted liquidity pressures on the micro-finance sector (OECD and European Commission, 2021). At the firm level, unemployment increased as jobs in key sectors such as construction, tourism, and manufacturing were lost. At the household level, micro-loan demand increased, exacerbating over-indebtedness⁸ and distress borrowing. However, three factors may have mitigated credit risk concerns. Repayment freezes on loans and interest accruals (e.g., microfinance loans) to alleviate the burden on distressed clients were implemented by financial authorities for a period of around ten months.⁹ Growing remittances may have played a fundamental role in alleviating the microfinance debt burden.¹⁰ The government offered a public loan program on February 2021 to support micro firms and women-owners

⁶ Survival analysis applied to credit risk has its origin in the early studies of Narain (1992) and Banasik et al. (1999).

⁷ Goedecke (2018) focuses on contagion risk and does not investigate the role of gender.

⁸ Over-indebtedness arises because additional debt requirements to mitigate pandemic costs impose additional burden to repay outstanding and new loans (Schicks, 2013).

⁹ In Mexico, the original repayment freeze program for bank loans was established for the period from March 25 to September 25, 2020 (see <https://www.gob.mx/shcp/prensa/comunicado-no-029>; last accessed June 15, 2022). However, an announcement by financial authorities on September 23, 2020 prolonged it until January 31, 2021 (see <https://www.gob.mx/cnbv/prensa/comunicado-conjunto-nuevo-paquete-de-medidas-para-reestructuracion-de-creditos>; last accessed June 15, 2022). Approximately, 8.6 million credits were benefited by this program. The size of the loan payment was reduced by 25 percent.

¹⁰ In fact, in 2021 Mexico became the second largest recipient of remittances in the world, achieving approximately 54 million dollars (see <https://www.migrationdataportal.org/themes/remittances>; last accessed June 16, 2022). This effect is particularly important for women since in this same year 16.1 percent of households headed by women were recipients of remittances (see <https://www.cemla.org/foroderemesas/notas/2022-06-notas-de-remesas.pdf>; accessed June 15, 2022).

of micro firms.¹¹ It is likely that these events may have boosted women loan repayment disproportionately. Our data have allowed us to study the link between gender disparities and microfinance loan repayment time during the pre-and post-COVID-19 crisis.

3. Empirical methods

This section includes the definition of microfinance loan default, the source of our data, a discussion of self-selection bias, the selection of explanatory variables, and the modeling technique.

3.1. Definition of microfinance group loan default

In the microfinance credit risk literature, most studies use a “30 days past due” criterion to define loan default.¹² This is because of the short-term nature of micro-finance loans. In fact, at the global level, most microfinance loans have a one-year maturity period (Zamore et al., 2019, p.4).¹³ The time frequency of group loans is split as 62 percent have a 7-day frequency, whereas the remaining 38 percent have a 15-day frequency. To compensate for differences in the time frequency payment, we use a definition wherein default occurs when at least three consecutive missed payments are registered. In our robustness test, we compared this definition with the “30-day and 90-day past due” criterion.^{14,15} We regard this definition as more adequate as it is more aligned with the time frequency of payments.

¹¹ The program provides a 25k individual loan to qualifying applicants (i.e., micro firms, individual borrowers (see <https://www.gob.mx/se/articulos/inicia-recepcion-de-solicitudes-para-el-programa-de-apoyo-financiero-para-microempresas-familiares-credito-a-la-palabra-2021>; accessed June 15, 2022).

¹² For example, see Beck et al. (2018) for a sample of an Albanian bank, Goedecke (2018) for a sample of Mexican banks, Zainuddin and Yasin (2020) for a sample of global banks, and Zamore et al. (2019) for a sample of global micro-finance institutions.

¹³ In Appendix A, we discuss how our definition relates to the one available in the Basel Accord.

¹⁴ Results are available upon request.

¹⁵ Annex 33 of the Mexican banking solvency rules text (CUB, its acronym in Spanish) establishes that the default should be registered depending on the loan’s number of days past due and the loan’s payment type as follows: (i) a “30-day past due” and the loan is a non-revolving single payment at maturity including interests, (ii) a “90-day past due” criterion in repayment of interests or “30-day past due” criterion in repayment of outstanding loan amount and the loan is non-revolving with a single capital payment at loan maturity with recurrent interest payments during the loan life cycle, (iii) a “90-day past due” criterion in repayment of either interests or capital and the loan is non-revolving and repaid with several frequent payments that reimburse both loan and capital.

We assume that there is no loan repayment after the loan is in default and loans cannot return to the paid-up status.

3.2. Data

We use various data sources in this paper. For example, we use proprietary loan-level data collected by Mexican financial authorities (i.e., Banco de México [*Banxico*, its acronym in Spanish] and the National Banking and Securities Commission [*CNBV*, its acronym in Spanish]). We can track the history of each loan and define alternative default definitions based on the time in arrears or delay of repayment. We also use publicly available macroeconomic data reported by a Mexican public sector entity (i.e., National Institute of Statistics and Geography [*INEGI*, its acronym in Spanish]). Our sample covers the period from August 2017 to August 2021. The proprietary-loan-level data is reported by the MFIs to Banxico using regulatory layouts on a bimonthly basis, which implies that all in all we have 25 periods (i.e., $t = 1, \dots, 25$).

There are five banks and two non-bank financial intermediaries that report microfinance-loan data.¹⁶ There are three important characteristics about this microfinance-loan market. First, Compartamos dominates the market share for group loans. In fact, Compartamos has a market share of 91.4 percent and 89 percent of the group micro-finance loans at the population level as measured by the number of loans granted and by the size of the outstanding loan portfolio as of February 28, 2021 (Banxico, 2021, pp.29–30).

Second, due to the confidential nature of our data, we do not report the market share of financial entities in our sample, but it is largely dominated by Compartamos in a similar proportion. Since the market share of some financial entities is very small, our random sampling technique is not able to incorporate loans granted by one bank and two non-bank financial intermediaries.

¹⁶ The five banks are Banco Azteca, Banco Compartamos, Banco Ahorro Famsa, Banco Afirme, and Banco Forjadores. The non-bank financial intermediaries are the Grameen Carso and Santander Inclusión Financiera. Banco Famsa lost its operating license in late June 2020 due to a number of internal mismanagement practices, including regulatory breaches (see the official financial authorities report at https://www.dof.gob.mx/nota_detalle.php?codigo=5595953&fecha=01/07/2020#gsc.tab=0; accessed on September 28, 2022).

Third, our sample could not cover a large number of entities that grant microfinance loans in Mexico.¹⁷ These entities operate with a diverse range of legal status.¹⁸ According to ProDesarrollo (2021), the microfinance sector is largely concentrated in six institutions that have a market share of approximately 74 percent, as measured by the sum of their loan portfolio as the numerator over the total value of the loan portfolio of all the intermediaries as the denominator. In particular, the three largest institutions have a share of 60 percent of the loan portfolio and 59 percent of the number of clients. Banco Compartamos is the largest institution, with a 39 percent market share as measured by the size of the gross loan portfolio and 41 percent as measured by the number of clients. According to ProDesarrollo (2021), women represent 96 percent of clients in products¹⁹ offered under group methodologies. In addition, the proprietary-borrower-characteristics data are also reported by commercial banks to Banxico. This dataset is highly confidential as it has borrower-specific information (e.g., gender, age, marital status, geographic location) of all bank customers having an outstanding loan granted by a Mexican bank.

At the population level, we have a large panel data set that has millions of observations for group loans. To construct the sample, we proceed as follows. First, we take a random sample without replacement of 500K customers from the proprietary-borrower-characteristics data. Our random sampling is programmed to ensure that there is no missing data.²⁰ Second, we use a group identification number that is assigned by each bank to each group customer to merge the proprietary-borrower-characteristic sample with the loan-level data. This identification number has two properties, it is unique and non-repeatable.

¹⁷ According to Antón-Díaz (2017), data of year end 2015 in Mexico suggest that the ten largest MFIs in Mexico had a share of 81 percent of the market, whereas approximately 1,500 smaller MFIs represented the remaining 19 percent.

¹⁸ According to the 60 MFIs that report data to ProDesarrollo (2021), in Mexico, there are a number of different types of institutional arrangements in addition to commercial banking that permit to offer this service such as both regulated and unregulated multiple purpose financial companies (SOFOMES, its acronym in Spanish), popular financial companies (SOFIPOS, its acronym in Spanish), popular financial societies (SOFINCO, its acronym in Spanish), Cooperative Societies of Savings and Credit (SOCAP, its acronym in Spanish), and Limited Liability Company (SPRDERL, its acronym in Spanish).

¹⁹ MFIs such as Compartamos offer additional primary insurance schemes to actual microfinance loan clients such as basic life insurance, health expenses insurance, theft insurance, and motor vehicles insurance (OECD, 2021, p.225).

²⁰ This is a requirement because survival techniques apply only to balanced panel data.

Moreover, this identifier is the same for all the bank products acquired by the group customer, and it is time invariant. Third, we drop observations with missing values from the merged sample, and we reduce the sample size to obtain a balanced panel. Fourth, we take a pseudo-random sample without replacement of 320K loans, grouping them by time period and gender.

Loan pseudo-random sampling by time period guarantees that the subsample is an independently and identically distributed sample of the bank population. In fact, our sampling uses time period as a grouping variable to keep a similar percentage of loans granted during the pre- and post-COVID-19 with a similar distribution overall, $t = 1, \dots, 25$. Since the proportion of bank microfinance loans granted to women is greater than to men, we also use gender as a grouping variable to ensure that the proportion of originated bank loans is similar between men and women. Table A1 in Appendix A shows the total number of microfinance loans originated in each period by gender.

Table 1 provides a summary of the loan sample characteristics. The group loan sample has approximately 198K loans with 406K observations. Since a client may have more than one loan, the maximum number of loans granted to a single client in our sample is 16. The group loan with the longest lifecycle or the maximum number of bimonthly periods per loan is 10.²¹

Table 1. Loan sample characteristics

No. banks	No. borrowers	No. loans	No. obs.	Max. no. loans per borrower	Max. no. of periods per loan
4	91,195	198,058	406,749	16	10

Source: Banco de México authors' calculations.

Notes: The sample has loans from a different number of banks. Although we do not report a breakdown of the market share per bank, Compartamos largely dominates the sample as measured by the loan number. Our sample does not incorporate loans granted by non-bank financial intermediaries (i.e., the Grameen Carso and Santander Inclusión Financiera) such as multiple purpose financial companies (SOFOMES, its acronym in Spanish). SOFOMES may be a subsidiary of a commercial bank or form a part of a financial group. SOFOMES can be characterized as intermediaries that originate any loan type but cannot take public deposits.

²¹ Assuming that each period consists of 60 days, 10 periods is approximately equal to 1.5 years.

3.3. Sample self-selection bias

Credit risk models suffer from at least one source of self-selection bias. Cader and Leatherman (2011) define three types of self-selection bias. First, research analyses that address determinants of firm entry or loan granting may fail to incorporate information of the firms that did not enter or loans that were not granted. Second, studies that analyze determinants of firm exit or loan performance may fail to incorporate the information of exited firms or loans that were securitized or sold to other financial intermediaries. Third, papers that investigate both firm entry and firm exit or loan granting and performance simultaneously may fail to incorporate information on surviving firms or surviving loans. The omitted data inevitably lead to biased coefficient estimates and loss of reliability on inference (e.g., a variable whose coefficient is insignificant may become statistically significant or vice versa), which inevitably lead to wrong conclusions. Heckman (1979) proposed a switching regression method to solve this problem. Cader and Leatherman (2011) highlight that this approach is limited because it fails to incorporate predictors that affect firm entry and exit or loan granting and exit. The study of Cader and Leatherman (2011) incorporates sample selection bias in firm-survival analysis that originates from excluding data of firms that exit. Unfortunately, the present study is also subject to at least one remaining source of sample selection bias. Our sample is subject to self-selection bias as we do not have information about the ratio of successful to unsuccessful loan applications. Hence, we have focused exclusively on actual loan borrowers and their arrears.

3.4. Selection of variables

Table A2 in Appendix A provides definitions of the variable. The dependent variable is the group loan's "time to default" or the duration of time it takes for a group of borrowers to default on their bank loans. In our study, due to the short-term nature of micro-finance loans, time is measured in days. For each loan record, we track its history and register the number of days elapsed since the time of loan origination. The data collection process can best be described as follows. In each bimonthly period, we construct a default status variable that tracks the payment history of each group loan. We use micro variable loan

characteristics (i.e., loan's size, real interest rate, term to maturity, group size, and a binary variable for restructured loans) and borrowers' characteristics (i.e., the gender, age, marital status, and state address).

We also construct two alternative aggregate past default rate indicators based on calendar time. The first is the actual cumulative loan default rate in time k ($CLDR_k$), while the second is the cumulative loan default rate by loan origination in time k ($CLDRO_k$). To the best of our knowledge, the choice of macroeconomic variables to control for systematic risk is not well-documented in the case of micro-finance loans. Hence, there is no consensus on which are the best control macro covariates. In this paper, we use consumers' confidence and the workers' remittances. The former provides a forward-looking measure of the economic outlook envisaged by individual economic agents, whereas the latter offers a measure of external funding sources that may assist individual obligors.

3.5. Parametric survival model

This section describes the parametric Accelerated Failure Time (AFT) survival models used in our analysis and how we interpret the covariate's marginal effect.

3.5.1. Survival analysis and accelerated failure time model

A certain proportion of micro bank loans may: (i) default, (ii) be repaid early, (iii) be restructured, or (iv) simply mature (i.e., be fully repaid at the end of the loan term). A standard survival analysis is designed with the assumption that all loans will default and there is no adjustment for the fraction of loans that perform.²² Survival analysis has been designed to deal with censored data. In fact, survival analysis assumes that censoring occurs randomly and there is no link with the factors that explain loan default. In our context, we have right-censored data. This implies that default is not observed for a large fraction of loans during the sample period.

The analysis time is not the same as the calendar time. Analysis time is not a simple date variable that is available in our data. Analysis time is defined by the researcher

²² In the literature, mixture cure rate models have been designed to incorporate an adjustment for the fraction of loans that perform.

specifically for survival analysis, and in our setting, it has been defined to capture the number of days since the onset of risk (i.e., the time at which the loan originated and risk began, and before the default or censored state occurs).²³

We collect data for the period starting August 2017 onward and include a small fraction of outstanding loans available from previous periods. If we assume that each loan has a history of $k = 1, \dots, m$ bimonthly periods and we have $j = 1, \dots, n$ loans in our data, then a trivariate response $(t_{0jk}, t_{jk}, d_{jk})$ is used to represent a loan record or the period of observation $(t_{0jk}, t_{jk}]$ ending in either failure ($d_{jk} = 1$) or right-censoring ($d_{jk} = 0$). Each loan has multiple records (i.e., observations) such that loan j in time k has x_{jk} covariate vector values. In this setting, the loan's survival or analysis time is associated with loan, borrower, past default rate, and macroeconomic characteristics not only when the loan originated but also during the loan's life. Let the random variable $T \in [0, \infty)$ be the loan's time to default. For a given survivor function, $S(t)$, the density function is obtained as $f(t) = -\frac{d}{dt} S(t)$, while the hazard function is obtained as $h(t) = \frac{f(t)}{S(t)}$. For each j th loan, it is possible to define for each k th point-in-time (i.e., observation) the survival time as a function of p explanatory variables as $S(t_{jk}) = S(t_{jk} | x_{1,jk}, \dots, x_{p,jk})$ and similarly define $f(t_{jk})$ and $h(t_{jk})$. A simple form to estimate the survival model is to use the AFT (Cleves et al., 2010, pp. 239–241) as shown in the following equation:

$$\ln(t_{jk}) = \beta_0 + \beta_1 x_{1,jk} + \dots + \beta_p x_{p,jk} + \ln(\tau_{jk}) \quad (1)$$

where t_{jk} is the time to loan default for loan j in time span (i.e., observation) k , and it is measured using days based on unit per loan record, β are the covariate coefficients to be estimated from the data using maximum likelihood technique (Cleves et al., 2010, pp. 245–246), x_{djk} are the time-varying or time-constant p covariates ($d = 1, \dots, p$), and $\ln(\tau_{jk})$ is a random quantity that follows an assumed parametric distribution with density $f()$.

²³ We discuss and elaborate on the difference between analysis time and calendar time in Notes 2 of Table A2 in Appendix A.

The shape of the parametric survival function depends on the distribution assumed for τ_{jk} .²⁴ For example, if we assume that τ_{jk} is distributed as lognormal with parameters β_0 and σ , (i.e., $\tau_{ji} \sim \text{lognormal}(\beta, \sigma)$), the AFT can be defined²⁵ as:

$$S(t_{jk} | x_{1jk}, \dots, x_{pjk}) = 1 - \Phi\left(\frac{\ln(t_{jk}) - (\beta_0 + \beta_1 x_{1jk} + \dots + \beta_p x_{pjk})}{\sigma}\right) \quad (2)$$

where $\Phi()$ is the CDF for the standard Gaussian (normal) distribution and σ is known as a strictly positive ancillary parameter.

3.5.2. Marginal effects

In this parametric survival framework, exponentiated coefficients are interpreted as time ratios for a 1-unit change in the corresponding exogenous variable. For example, if the time ratio is defined as t_j^*/t_j and if the loan has x_1 increased by 1, then

$$\frac{t_j^*}{t_j} = \frac{\exp(\beta_1(x_1 + 1) + \dots + \beta_p x_p) \tau_j}{\exp(\beta_1 x_1 + \dots + \beta_p x_p) \tau_j} = \exp(\beta_1) \quad (3)$$

Hence, as a result of a 1-unit increase in x_1 , the time ratio is a factor that is used to multiply the expected time to default. On the one hand, if $\exp(\beta_1) < 1$ (i.e., $\beta_1 < 0$), the expected time decreases, or the covariate accelerates the effect of time, time passes faster, and loan default is expected to occur sooner (i.e., credit risk increases). On the other hand, if $\exp(\beta_1) > 1$ (i.e., $\beta_1 > 0$), the expected time increases or the covariate decelerates or degrades the effect of time, time passes slower, and loan default is expected to occur later (i.e., credit risk decreases).

In economics, most of the time the parameter of the greatest interest is the impact of one standard deviation increase in x_1 (Cleves et al., 2010, p.240). Following the same principle, as a result of a one standard deviation increase in x_1 , the time ratio

²⁴ STATA can fit up to six parametric models: exponential, Weibull, Gompertz, log-normal, log-logistic, and generalized gamma (see Cleves et al. (2010, pp. 245–282) for details).

²⁵ Since covariates accelerate time by a factor $\exp(-(\beta_0 + \beta_1 x_{1jk} + \dots + \beta_p x_{pjk}))$, Cleves et al. (2010, p. 270) show that the survival function can be derived as shown in eq. (2).

that is used to multiply the expected time to default is $\exp(\beta_1 \sigma_{x_1})$. In addition, the interaction effect that arises as a result of a one unit increase in x_1 is computed with the time ratio as $\exp(\beta_1)$. In the presence of interaction terms, we use either $\exp(\beta_1 \sigma_{x_1} + \beta_2 \sigma_{x_1})$ or $\exp(\beta_1 + \beta_2)$, where β_2 is the coefficient for the interaction term, for a one standard deviation and a one unit increase in x_1 , respectively. In this paper, we compute the impact of a one standard deviation increase and a one unit in x_1 .

4. Results and discussions

Our analysis starts with a discussion of the microfinance loan survival function by gender.²⁶ We also present our multivariate regression results for the AFT models under consideration and focus on size, sign, and statistical significance of coefficients along with the model's fit.

4.1. Microfinance loan survival function per gender

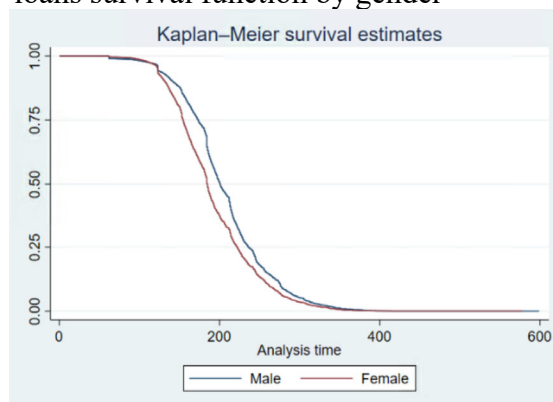
We compare the equality of loan survivor functions by gender to assess the decay of the survival rate. Figure 1 shows that the survival rate of microfinance group loans to females decays at a faster rate, suggesting that females default sooner. As expected, there is an overlap during the initial and final periods. Table A3 in Appendix A shows the estimates for the mean and median survival times for microfinance group loans. Based on the payment frequency default definition, it is clear that the female median survival time for group loans is 16 days shorter (i.e., 185 days for female compared with 201 days for male).²⁷ A difference of 16 days is not negligible as this time span is almost equivalent to the time it takes a default event to occur for microfinance group loans that are repaid every week (e.g., the frequency of payment of microfinance group loans is 7 or 15 days;

²⁶ In Appendix A, we discuss descriptive statistics of our covariates and the correlations. We also discuss the criterion used for selecting an appropriate distribution for the parametric AFT survival model.

²⁷ The 95 percent confidence interval suggests that the population median survival time for group loans is somewhere between [184, 185] and [199, 202] for female and male borrowers, respectively. This result suggests that the difference in median survival time between female and male borrowers can increase up to 18 days.

approximately 56.06 percent of the observations in our sample have a 7-day repayment frequency, whereas the remaining 43.94 percent have a 15-day repayment frequency). These new results suggest that the gender survival rate matters for group loans as female borrowers default at an earlier stage. This is an interesting result because we have to identify the factors or predictors that explain it.

Figure 1. Kaplan-Meier micro group loans survival function by gender



Source: Banco de México, authors' calculations.

Notes: This figure reports the evolution of the estimated survivor curve using the Kaplan-Meier estimator for bank loans to micro groups by gender. The Y-axis shows the survival rate in percent. Here “analysis time” represents the lifetime of group loans in days. This figure reports the estimator for bank loans to groups using the default definition based on payment frequency.

Unfortunately, it is not immediately clear to determine from a visual inspection whether the survival curves differ in statistical terms by gender. Table A4 in Appendix A shows the results of three nonparametric tests²⁸ to compare survival curves for group loans by gender for our default definition as discussed in Section 3.1. The results show that the survival curves between female and male microfinance loans differ statistically for group loans independently of the loan definition and the test type under analysis at the 1 percent level.

²⁸ We show the results of the Log-rank, Wilcoxon, and Tarone-Ware (Cleves et al., 2010, p.122).

An issue of concern is related to the impact of the COVID-19 pandemic on calendar time default rate statistics. A closer inspection of the evolution of the two aggregate loan default rates estimators per gender is available in Panels A and B in Figure 2. We appreciate that there is a difference depending on the estimator under analysis. Panel A in Figure 2 shows that there is a spike in August 2020 for $CLDR_k$, whereas Panel B in Figure 2 shows that there are three spikes for $CLDRO_k$ that occur in December 2019 and February and April 2020. The fact that $CLDRO_k$ has an earlier spike is expected as this estimator uses loans at the time of origination, which occurs in an earlier period. Interestingly, the impact of COVID-19 on aggregate loan default rate has waned over time starting in 2021, possibly due to a combination of government policies irrespective of the loan type and the estimator under analysis. The evolution of group loans shows a higher default rate level for males in all periods.

4.2. Multivariate parametric survival analysis models

In this section, we discuss our parametric log-normal multivariate survival analysis models.²⁹ Our strategy can be described as follows. First, we fit the AFT survival model as described in eq.(1), Section 3.5.1, using gender as our unique explanatory variable. We also assess the robustness of the coefficient estimate and introduce state and COVID-19 pandemic. Then, for our baseline model, we introduce loan and borrower characteristics and assess both the contribution of microeconomic variables and its interactions. Next, we analyze dynamics or persistence in our model at the sector level and introduce two proxy variables for the aggregate lagged calendar time default rates.³⁰ After that we introduce macroeconomic explanatory factors. Finally, we report results of our robustness tests.

Table 2 presents the coefficient estimates for the model including gender as the unique explanatory factor. We want to assess how robust is our gender coefficient. In other words, we want to assess what happens to eq.(1) when only the gender variable is included

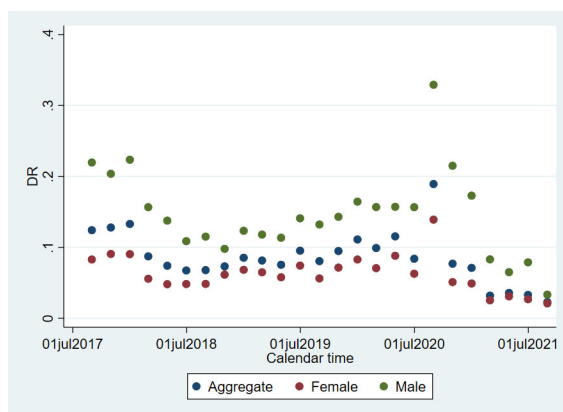
²⁹ In Appendix B, we use the Akaike Information Criterion (AIC) to justify the choice of the parametric lognormal survival model over other possible alternatives.

³⁰ These two variables also serve as a proxy for contagion risk as discussed by Iyer and Puri (2012) and Goedecke (2018).

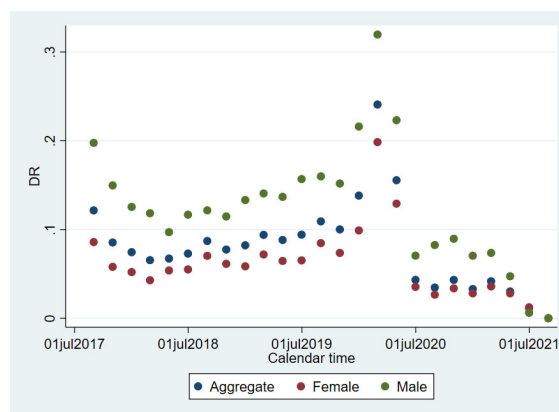
as an explanatory factor as some of our control variables may be correlated with each other. Columns (2) to (5) in Table 2 show the coefficient estimates for group loans.

Figure 2. Evolution of calendar loan default rates for microfinance group borrowers

Panel A. Calendar loan default rate



Panel B. Calendar loan default rate by origination period



Source: Banco de México, authors' calculations.

Notes: This figure reports the evolution of the two calendar time default rates for microfinance group borrowers. The Y-axis shows the default rate in percent. Here “calendar time” is reported on a bimonthly basis. This figure reports the estimator for bank loans to groups using the default definition based on payment frequency.

According to Column (2) in Table 2, the coefficient estimate for gender is both negative and statistically significant at the 1 percent level for group loans. Table C1 in Appendix C shows the marginal effects for both a one standard deviation increase and one unit increase in gender for the univariate regression. The coefficient estimate suggests that a one unit (standard deviation) increase in gender if the obligor is a female decreases the expected time by a factor of 0.96 (0.98), the time passes faster, and the loan default is expected to occur sooner (i.e., credit risk increases).³¹

³¹ The difference in the conditional median survival time estimate for group loans that include only gender as explanatory factor reduces to 8 days (194 days for females, 202 days for males). However, no overlapping between the 95% confidence interval for the conditional median survival time estimates per gender suggests that this difference is still statistically significant at the 1% level.

Columns (3) and (4) in Table 2 show the coefficient estimates when bimonthly calendar time fixed effects along with state fixed effects are included.³² The coefficient estimate remains robust when state fixed effects are included. However, its value is affected when calendar time fixed effects are included. In fact, credit risk increases as a 1-unit (standard deviation) increase in gender decreases the expected time by a factor of 0.93 (0.97).

Column (5) in Table 2 shows the coefficient term for the COVID-19 period and its interaction with gender. The health crisis due to the COVID-19 has exerted a large effect on the time to default. A 1-unit (standard deviation) increase due to the Covid-19 period reduces the expected time by a factor of 0.76 (0.87) for group loans. Moreover, the marginal effect analysis for the interaction term between COVID-19 and gender suggests that there is no evidence of an asymmetric response depending on the borrower's gender as the coefficient remains statistically insignificant.

Column (2) in Table 3 shows the coefficient estimates for the baseline model, which include microeconomic variables (i.e., loan and borrowers' characteristics) for microfinance group loans. The coefficient estimate of gender for group loans is negative and statistically significant at the 1 percent level, whereas the size of the marginal effect remains similar compared with previous univariate estimates. Specifically, Table C2 in Appendix C shows that the coefficient estimate suggests that if the obligor is a female, then a one standard deviation increase in gender increases the expected time by a factor of 0.98 for group loans, the time passes faster, and the loan default is expected to occur sooner.

For simplicity, we use a one standard deviation increase in the microeconomic covariates to compare the size effect across micro covariates (see Table C2 in Appendix C). Excluding group size, all remaining micro covariate coefficients are statistically significant (at least) at the 10 percent level. The following covariates have a marginal effect that is

³² Each individual bank loan may have originated in any of 32 Mexican states. State fixed effects are used as control for time invariant heterogeneity across states. They also serve to mitigate endogeneity concerns attributed to omitted variable bias at the state level. Examples of state fixed effects are time invariant characteristics such as local government quality and institutional quality; population, size, and firm-industry presence; endowment of natural resources; and proximity to foreign commercial partners. Using granular time-fixed effects is useful as a means to control for underlying observable and unobservable systematic differences (i.e., time shocks) between observed calendar time units. In other words, we control for time-varying business cycle effects.

Table 2. Univariate AFT survival models for bank loans to micro group borrowers

Variables	Group loans			
1	2	3	4	5
Gender _j	−0.0413 ^a (0.0039)	−0.0365 ^a (0.0039)	−0.0742 ^a (0.0030)	−0.0581 ^a (0.0071)
Covid _k				−0.2785 ^a (0.0101)
Covid _k * Gender _j				−0.0117 (0.0077)
Bimonthly Time FE	No	No	Yes	Yes
State FE	No	Yes	Yes	Yes
Chi ² statistic	112 ^a	393 ^a	29,741 ^a	36,441 ^a
LogLikelihood	−18,148	−18,012	−11,805	−11,235
N _{1-F} (# of loans)	198,058	198,058	198,058	198,058
N _{2-F} (# of obs)	406,749	406,749	406,749	406,749
D _F # of defaults	15,019	15,019	15,019	15,019

Source: Banco de México, authors' calculations.

Notes: a, (b), and [c] are significant at 1%, (5%), and [10%], level, respectively (two-sided test). This table displays the estimates for bank microfinance loans to group borrowers. All estimations are based on eq.(1): $\ln(t_{jk}) = \beta_0 + \beta_1 x_{1,jk} + \dots + \beta_p x_{p,pjk} + \ln(\tau_{jk})$, and follow the same loan default definition as discussed in Section 3.1. The standard errors are computed using the Huber-White/sandwich estimator. This estimator is robust to some type of misspecifications so long as the observations are independent. The Chi-squared statistic values reported in the model's goodness of fit are obtained using the Wald test. The subscript F for the number of loans (N_{1-F}), number of observations (N_{2-F}), and number of defaults (DF) is used to define that these statistics were computed for the full sample.

associated with an increase in credit risk for group loans: real interest rate (0.99), group size (1.00), and marital status (0.99). Interestingly, the marginal effect of gender induces more credit risk than any other micro covariate for group loans. The following microeconomic covariates have a marginal effect that is associated with a decrease in credit risk for group loans: term to maturity (1.28 for TtM = 2, 1.49 for TtM = 3, 1.83 for TtM = 4), restructured loans (1.05), loan size (1.01), and borrower's age (1.01). The impact of the loan's term to maturity increases with the loan's TtM category, and it dominates as it is greater in absolute value compared with any other covariate coefficient.

Table 3. Multivariate AFT survival models for bank microfinance loans to group borrowers

Variables	Group loans
1	2
Gender _j	−0.0474 ^a (0.0022)
Real interest rate _{j,k}	−0.0442 ^a (0.0085)
Term to maturity _{j,k} = 2	0.2200 ^a (0.0047)
Term to maturity _{j,k} = 3	0.3533 ^a (0.0044)
Term to maturity _{j,k} = 4	0.5378 ^a (0.0045)
Loan size _j	0.0133 ^a (0.0018)
Group size _j	−0.0004 ^b (0.0002)
Restructured _{j,k}	0.1842 ^a (0.0072)
Age _{j,k}	0.0009 ^a (0.0001)
Marital Status _{j,k}	−0.0227 ^a (0.0019)
Covid _k	−0.1842 ^a (0.0061)
Bimonthly time FE	Yes
State fixed effects	Yes
Chi ² statistic	122,721 ^a
LogLikelihood	−5,155
N _{1-F} (# of loans)	198,058
N _{2-F} (# of observations)	406,749
D _F # of defaults	15,019

Source: Banco de México, authors' calculations.

Notes: a, (b), and [c] are significant at 1%, (5%), and [10%] level, respectively (two-sided test). This table displays the multivariate estimates for bank microfinance loans to group borrowers, using microeconomic (i.e., borrowers and loan characteristics) variables. All estimations are based on eq.(1): $\ln(t_{jk}) = \beta_0 + \beta_1 x_{1,jk} + \dots + \beta_p x_{p,jk} + \ln(\tau_{jk})$, and follow the same loan default definition as discussed in Section 3.1. The Chi-squared statistic values reported in Model's goodness of fit are obtained using the Wald test. The subscript F for the number of loans (N_{1-F}), the number of observations (N_{2-F}), and the number of defaults (D_F) is used to define that these statistics were computed for the full sample.

We explore interaction effects among microeconomic covariates with gender to gain more insight into potential disparity effects. To avoid multicollinearity, we investigate individual interaction effects. We estimate seven multivariate regression and interact each of six microeconomic variables (i.e., real interest rate, TtM, loan size, group size, restructured, age, marital status) with gender per loan type and report the interaction coefficient per regression.

Column (2) in Table 4 shows the estimates of the coefficient for individual interaction effects. Column (2) in Table 4 shows that the coefficient for the interaction term of gender with real interest rate and restructured is positive and statistically significant at the 1 percent level. This result suggests that the effect of female borrowers is associated with less credit risk in terms of time to loan repayment for group loans.

Column (2) in Table 4 shows that the coefficient for the interaction term with term to maturity and borrower's age is negative and statistically significant at the 1 percent level. This result suggests that female borrowers are associated with more credit risk in terms of time to group loan repayment.

Column (2) in Table 4 shows that the coefficient for the interaction term with the loan's size and borrower's marital status is not statistically significant, which suggests that these two interaction variables may be neglected for group loans. An interaction variable should be included in the survival if both the variable's coefficient and its interaction term are significant and if the size of the marginal effect is meaningful in an economic sense.

Table C3 in Appendix C shows the marginal effect analysis including interaction terms between gender and micro control variables. The results suggest that only the loan's term to maturity satisfies this criterion. The interaction of time to maturity reduces credit risk for female borrowers as its sign is positive and increases with the loan's TtM. This result coincides with the previous findings of Karlan and Zinman (2008), which show that longer maturity loans are preferred by microfinance borrowers as this means a lower cut from their time-varying budget and consumption level. In fact, Karlan and Zinman (2008) find that borrowing is more sensitive to the term to maturity compared with any other loan covariate such as interest rates. Based on international evidence, regulators that intend to

introduce bank incentives to reduce regulatory costs for female borrowers should opt to include an interaction term with loan's term to maturity.

Table 4. Univariate interaction effects for Multivariate AFT survival models for bank microfinance loans to group borrowers

Variables	Group Loans
1	2
Gender _j * Real interest rate _{j,k}	0.1160 ^a (0.0183)
Gender _j * TtM _{j,k} = 2	-0.0499 ^a (0.0075)
Gender _j * TtM _{j,k} = 3	-0.1032 ^a (0.0061)
Gender _j * TtM _{j,k} = 4	-0.1580 ^a (0.0059)
Gender _j * Loan size _j	-0.0005 (0.0037)
Gender _j * Restructured _{j,k}	0.0550 ^a (0.0059)
Gender _j * Age _{j,k}	-0.0005 ^a (0.0001)
Gender _j * Marital Status _{j,k}	-0.0032 (0.0040)
Bimonthly time FE	Yes
State fixed effects	Yes
Micro and covid controls	Yes
N _{1-F} (# of loans)	198,058
N _{2-F} (# of observations)	406,749
D _F # of defaults	15,019

Source: Banco de México, authors' calculations.

Notes: a, (b), and [c] are significant at 1%, (5%), and [10%] level, respectively (two-sided test). This table displays the univariate interaction effects for multivariate estimates for bank microfinance group loans, using microeconomic (i.e., borrowers and loan characteristics) variables. All estimations are based on eq(1): $\ln(t_{jk}) = \beta_0 + \beta_1 x_{1,jk} + \dots + \beta_p x_{p,jk} + \beta_1 (x_{1,jk} \times \text{Gender}_j) + \ln(\tau_{jk})$, and follow the same loan default definition as discussed in Section 3.1.

Table 5 presents the coefficient estimates that result when including calendar aggregate loan default rate variables lagged one period (i.e., 60 days) for the banking

microfinance sector in the model. We use two estimators for the calendar aggregate loan default rate. The first estimator is the cumulative loan default rate ($CLDR_k$), whereas the second is based on the cumulative loan default rate by loan origination ($CLDRO_k$). Columns (2) to (5) in Table 5 show the estimated coefficients. Columns (3) and (5) in Table 5 show the estimated coefficients for the interaction term with gender.

As expected, all coefficients of the default rate have a negative sign and all are statistically significant at the 1 percent level. The size of all lagged default rate coefficients is large compared with the microeconomic factors characterized by a negative coefficient sign, which suggests that the effect of this variable dominates. Table C4 in Appendix C shows the corresponding marginal effects. A one standard deviation increase in the lagged $CLDR_k$ of group loans is associated with a factor decrease of 0.80 in the time to default. The corresponding factor for $CLDRO_k$ is 0.84, which suggests that the effect is similar between the two loan default rate estimators. As expected, this result suggests that the expected time decreases, the time passes faster, and the loan default is expected to occur earlier (i.e., credit risk increases) when any of the two calendar aggregate default rates increase.

Regarding the interaction effect with gender, Columns (3) and (5) in Table 5 show that there is a positive coefficient sign for the interaction term based on the $CLDR_k$ estimator. In any case, Table C4 in Appendix C shows that the interaction effect factor between gender and the two loan default rate estimators suggests that the value of the factor may increase or decrease in absolute value by approximately 0.01, which is regarded as small, albeit statistically significant. This suggests that the choice of the estimator is not relevant for credit risk purposes.

Table 6 presents the coefficient estimates that result when two macroeconomic variables (i.e., consumer confidence and remittances) are included into the model. All macroeconomic variables are computed in annual change in percent.³³ This is because these variables are more likely to be stationary, and it is more interesting and easier to compare

³³ The annual change in percent is denoted as $\nabla_{12}(\%) = (1-L^{12})/L^{12} \cdot 100$, where the twelve-month difference operator is based on the lag operator L .

the effect of the annual rate of change than the change in the variable measured in level. All macroeconomic variables are lagged one period.

Table 5. Multivariate AFT survival model for bank microfinance loans to group borrowers.

Variables	Group loans			
1	2	3	4	5
	CLDR	CLDR	CLDRO	CLDRO
Gender _{<i>j</i>}	−0.0474 ^a (0.0022)	−0.0776 ^a (0.0049)	−0.0501 ^a (0.0024)	−0.0606 ^a (0.0042)
Default rate _{<i>k-1</i>}	−5.1510 ^a (0.0855)	−5.4312 ^a (0.0952)	−3.3439 ^a (0.0612)	−3.4408 ^a (0.0695)
Default rate _{<i>k-1</i>} *Gender _{<i>j</i>}		0.03090 ^a (0.0446)		0.1263 ^a (0.0389)
Bimonthly time FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Micro controls	Yes	Yes	Yes	Yes
Chi ² statistic	120,725 ^a	117,146 ^a	99,274 ^a	99,584 ^a
LogLikelihood	−5,583	−5,560	−5,769	−5,764
N _{1-F} (# of loans)	198,058	198,058	184,529	184,529
N _{2-F} (# of observations)	406,749	406,749	380,940	380,940
D _F # of defaults	15,019	15,019	14,428	14,428

Source: Banco de México, authors' calculations.

Notes: a, (b), and [c] are significant at 1%, (5%), and [10%] level, respectively (two-sided test). This table displays the multivariate estimates for bank microfinance loans to group, using the baseline model with two alternative past default rate variables (see Table A2 in Appendix A for variable definitions). All estimations are based on eq.(1): $\ln(t_{jk}) = \beta_0 + \beta_1 x_{1,jk} + \dots + \beta_p x_{p,jk} + \ln(\tau_{jk})$, and follow the same loan default definition as discussed in Section 3.1. Some microeconomic control variables are suppressed for simplicity from the output table, but available upon request. Columns (2) to (4) present the baseline model for group loans. The interaction effects of past default rate proxy and gender are included. The Chi-squared statistic values reported in Model's goodness of fit are obtained using the Wald test. The subscript F for the number of loans (N_{1-F}), the number of observations (N_{2-F}), and the number of defaults (DF) is used to define that these statistics were computed for the full sample.

Interaction effects are omitted as there is no reason to believe that macroeconomic factors have a different effect depending on the borrower's gender. We included annual time or calendar year fixed effects to control for time-varying business cycle effects that may not be captured with macroeconomic variables. Columns (2) and (4) in Table 6 show

the coefficient estimates using the lagged $CLDR_k$, whereas Columns (3) and (5) in Table 6 show the corresponding results for the lagged $CLDRO_k$. Table 6 shows that the coefficient estimates for gender including micro, industry, and macro controls remain robust compared with estimates available in Table 2.³⁴

As expected, Table 6 shows that the coefficient estimate for the annual change in remittances is positive and statistically significant at the 1 percent level, irrespective of the loan type. This supports the idea that an increase in the annual flow of remittances increases domestic consumption. Our results support the perception that the continuous increase in remittances during our period may have been used by microfinance borrowers to repay loans. Table C5 in Appendix C shows the corresponding marginal effect. A one standard deviation increase in the lagged annual percent change of remittances is associated with a factor of 1.04 [1.02] for group loans.³⁵ As expected, using alternative default rate estimators does not affect the main result.

Surprisingly, we have opposite signs for the coefficient of consumer confidence in the case of group loans. Column (2) in Table 6 shows that the sign of the coefficient for consumer confidence is negative and statistically significant at the 1 percent level for group loans. However, the size of this coefficient is small. For instance, Table C5 in Appendix C shows that a one standard deviation increase in the consumer confidence index is associated with a factor of 0.99 [1] for group loans, which confirms that the effect of this variable is negligible. Overall, the size of the effect of all macroeconomic factors is small compared with both aggregate calendar time loan default rates and a few microeconomic variables such as term to maturity or restructured loans.³⁶ We conclude that including macroeconomic variables is relevant, but the overall effect on borrower's time to default repayment capacity is less than expected.

³⁴ The difference in the median time to default estimate between female and male borrowers for group loans reduces to 7 days. This difference is statistically significant at the 1 percent level.

³⁵ We use \square to refer to estimates based on the calendar time aggregate loan default rate at the time of loan origination.

³⁶ In unreported results, we also used other macro variables such as a proxy for GDP both at the economy-wide level and at the state level; we also used remittances at the state level. GDP is not a forward-looking measure, and consumer's confidence is our preferred choice. The inflation rate is incorporated in the loan's real interest rate.

Table 6. Multivariate AFT survival model for bank microfinance loans to group borrowers

Variables	Group loans	
	1	2
Gender _j	−0.0454 ^a (0.0024)	−0.0444 ^a (0.0025)
COVID _k	−0.0846 ^a (0.0052)	−0.0979 ^a (0.0066)
Default rate _{k−l}	−0.8666 ^a (0.0400)	−0.4848 ^a (0.0331)
∇ ₁₂ Remittances _{k−l}	0.0042 ^a (0.0002)	0.0023 ^a (0.0002)
∇ ₁₂ Consumer conf _{k−l}	−0.0004 ^a (0.0001)	0.0005 ^a (0.0001)
Annual time FE	Yes	Yes
State FE	Yes	Yes
Micro controls	Yes	Yes
Chi ² statistic	78,115 ^a	72,859 ^a
LogLikelihood	−7,118	−6,816
N _{1-F} (# of loans)	198,058	184,529
N _{2-F} (# of observations)	406,749	380,940
D _F # of defaults	15,019	14,428

Source: Banco de México, authors' calculations.

Notes: a, (b), and [c] are significant at 1%, (5%), and [10%] level, respectively (two-sided test). This table displays the multivariate estimates for bank microfinance loans to group borrowers, using the baseline model with two macroeconomic control variables and two past default rate variables. All estimations are based on eq.(1):

$$\ln(t_{jk}) = \beta_0 + \beta_1 x_{1jk} + \dots + \beta_p x_{pjk} + \ln(\tau_{jk}), \text{ and follow the}$$

same loan default definition as discussed in Section 3.1. Column (2) presents the baseline model for group microfinance loans for macroeconomic variables and the calendar loan default rate, whereas the remaining Column (3) shows the corresponding results when using the calendar origination loan default rate for group microfinance loans, respectively. Interaction effects are omitted as there is no reason that supports the idea that macroeconomic factors exert a different effect for the loan gender. The Chi-squared statistic values reported in Model's goodness of fit are obtained using the Wald test. The subscript F for the number of loans (N_{1-F}), the number of observations (N_{2-F}), and the number of defaults (DF) is used to define that these statistics were computed for the full sample.

4.3. Hazard decomposition

In this section, we use a multivariate regression decomposition technique for hazard rate models developed by Powers and Yun (2009).³⁷ In contrast to the accelerated failure time approach, which relies exclusively on individual data at the loan level, this decomposition analysis utilizes aggregate data. The idea is to find sources of group disparities and changes over time to decompose the difference in loan default rates. In our context, the objective is to find group differences in levels of loan and borrowers' characteristics and group differences in the effects (i.e., coefficients from a multivariate model) of those characteristics on loan default rate differentials across gender. We estimate the model using a discretization of the borrower's age as a reference category for the dummy variables that define different constant hazards common to both loan groups by gender. We identify the variables that have the largest contribution to the overall difference in terms of both characteristics and coefficients. In addition, we analyze the baseline hazard contribution based on the borrower's age.

The estimated difference in the loan default crude rate³⁸ between men and women is 3.28 percent.³⁹ To simplify the presentation of estimated coefficients, we multiply this difference by 100 to show the increase or decrease in the gender gap loan default rate in terms of 3.28 defaults (per borrower's age) per 100 loans. In practice, for estimation purposes, we have to choose between female and male to define the comparison group and the reference group. This choice may lead to a difference in the results. To circumvent this issue, Powers and Yun (2009) proposed estimating the average between the two sets of estimates. We follow this recommendation and omit reporting both sets of separate decomposition results. Table 7 presents the decomposition results obtained by averaging the results of separate decompositions with interchanged reference and comparison groups. A positive explained component E_K (i.e., contribution to the total differential due to group

³⁷ We thank an anonymous reviewer for suggesting this constructive extension and for informing us how to do it with STATA.

³⁸ The higher-risk group consists of bank loans to male borrowers ($r_m = 0.06045$), whereas the lower-risk group comprises bank loans to female borrowers ($r_w = 0.02770$). The crude rate is estimated with all of the loan records (i.e., observations) available in the sample. This differs from mean rate statistics reported in Table A5, where we use only the last record for each loan.

³⁹ $r_m - r_w = 6.045\% - 2.77\% = 3.28\%$.

differences in the mean values of x) indicates that the loan default gender gap rate decreases when the group difference in variable k disappears. The unexplained component C_k (i.e., group differences in behavioral responses to the characteristics) has a similar interpretation. A positive coefficient indicates an expected decrease in the gender gap due to equalizing an effect to the male level. Panel C in Table 7 shows that the compositional differences between male and female borrowers contribute 4.00 defaults per 100 loans (122.20%) to the overall gap, whereas male and female differences in covariate effects contribute -0.73 defaults per 100 loans (-22.20%).

Panel A in Table 7 shows that among the explained components in the model, the most considerable differences in the gender gap arise due to differences in the real interest rate, time to maturity, and COVID-19. The difference in real interest rate by gender accounts for 1.08 defaults per 100 loans, representing 32.84 percent of the total gender gap in rates. At the aggregate level, the term to maturity contributes 2.02 defaults per 100 loans or 61.66 percent to the gap. Finally, COVID-19 has the largest effect since it accounts for 2.42 loans or 73.83 percent.

Panel A in Table 7 shows that the variables with the most considerable effects in the unexplained component are similar to those in the explained components. The results show that the overall gender gap would be expected to increase by 3.47 defaults per 100 loans (106.05%) if men and women benefited from the same real interest rate. Additionally, at the aggregate level, the gender gap in the number of defaults per 100 loans would be expected to decrease by 4.58, or 139.81 percent of the overall gap, if men and women had the same term to maturity. In contrast, if men and women had reacted the same to COVID-19, the Covid-19 crisis would have been expected to decrease the gender gap by 1.71 defaults per 100 loans (53.37%).

Panel B in Table 7 shows that the characteristics effects of the baseline hazard are at first positive and then negative. This reflects the fact that the age distribution of defaults is centered at an older age and a younger age for male and female borrowers, respectively. Taken together, age accounts for -0.01 defaults per 100 loans (0.33%) of the gender gap. The coefficient effects of the baseline hazard are informative about the contribution of gender differences in the age-specific baseline hazard rates to gender gap in default rates.

Table 7. Multivariate Decomposition into Characteristics (E) and Coefficients (C) Components

	95% CI				95% CI			
	E ($\times 100$)	Lower	Upper	Percentage of total	C ($\times 100$)	Lower	Upper	Percentage of total
<i>Panel A: Covariates</i>								
Term to maturity _{j,k} = 2	0.154 ^a	0.126	0.182	4.701	0.920 ^a	0.538	1.303	28.108
Term to maturity _{j,k} = 3	0.197 ^a	0.161	0.234	6.031	1.711 ^a	1.046	2.377	52.263
Term to maturity _{j,k} = 4	1.668 ^a	1.615	1.721	50.931	1.946 ^a	1.200	2.693	59.442
Real interest rate _{j,k}	1.075 ^a	0.936	1.215	32.839	-3.473 ^a	-4.992	-1.953	-106.048
Loan size _j	0.161 ^a	0.135	0.188	4.992	-0.669 ^a	-1.148	-0.189	-20.417
Group size _j	0.235 ^a	0.096	0.374	7.188	0.544 ^a	0.209	0.879	16.604
Restructured _{j,k}	0.000	-0.001	0.001	0.010	0.318 ^a	0.194	0.442	9.711
Marital Status _{j,k}	0.022 ^a	0.017	0.027	0.674	0.108 ^c	-0.020	0.236	3.297
Covid _k	2.418 ^a	2.236	2.599	73.831	1.715 ^a	1.027	2.403	53.373
Bimonthly time FE			Yes				Yes	
State FE			Yes				Yes	
<i>Panel B: Baseline Hazard Age Intervals</i>								
Age _{j,k} = 1 [18,40]	0.165 ^a	0.142	0.187	5.031	-2.613 ^a	-4.002	-1.223	-79.783
Age _{j,k} = 2 (40+]	-0.175 ^a	-0.198	-0.153	-5.358	-2.462 ^a	-3.777	-1.147	-75.188
<i>Panel C: Overall Contributions</i>								
	$\sum E_k = 4.001$			122.198	$\sum C_k = -0.727$			-22.198
	95% CI				95% CI			
	[3.997, 4.006]				[-0.760, -0.694]			

Source: Banco de México, authors' calculations.

Notes: a, (b), and [c] are significant at the 1%, (5%), and [10%] levels, respectively (two-sided test). The percentage of total is the percentage share of the differential in crude rates of 3.28 (per borrower's age) per 100 loans between men (4.00 defaults per 100 loans) and female (-0.73 defaults per 100 loans). All estimations are based on eq.(11) of Powers and Yun (2009, p. 241). The results are the average of two decompositions as suggested by Powers and Yun (2009). We use the command "hazdcmp" available in STATA to estimate the model. We thank Professor Powers for sharing the code to compute the average of the two decompositions. We excluded the conventional constant intercept and estimated the proportional hazard model with piecewise constant hazards over a variable with two age intervals in STATA to account for baseline hazard age intervals.

Taken together, gender differences in the logged baseline hazards account for about -5.075 defaults per 100 loans (-154.97%) of the gender gap. This is the expected reduction in the gap if male borrowers were to experience the same age-specific baseline rates as female borrowers.

4.4. Robustness test

To assess the strength of our findings, we investigate what is the impact of using alternative default definitions on the non-parametric survival curve per gender.

Specifically, we analyze what happens when 30 and 90 days past due loan default definitions are used instead of three consecutive non-payment periods based on payment frequency.⁴⁰ The results suggest that a change in default definition is very relevant for group loans.⁴¹ Table A3 in Appendix A shows that the restricted mean estimate is more sensitive to a change in the loan default definition as the difference between female and male borrowers in time to default increases from 14 to 45 days when we switch from the payment frequency default definition to 90 days past due. Perhaps this result is driven by the fact that the payment frequency for group loans varies between 7 and 15 days. Overall, we conclude that there is enough evidence to confirm that the survival curve by gender differs independently of the loan default definition under consideration. Moreover, taking a Basel II definition (i.e., 90 days past due) may intensify our previous findings as gender leads to a stronger discrepancy between male and female survival curves.

5. Conclusion

This paper is, to the best of our knowledge, the first to explicitly perform a comprehensive analysis that considers the role of gender disparities in microfinance

⁴⁰ A discussion of default definitions is available in Appendix A. The results are available in Figures A1 and A2 and in Table A3 and A4 in Appendix A. A visual inspection of Figures A1 and A2 in Appendix A suggests that the shape of the survival curve per gender may vary for group loans depending on the loan default definition under analysis. Table A3 shows that the median time to default estimate for male (female) borrowers increases from 190 (184) to 283 (307) days when switching from 30 to 90 days past due default definition for group loans. In other words, the difference in the median time to default unconditional estimate increases from 6 to 24 days for group loans.

⁴¹ Table A4 shows the results of three tests to compare whether survival curves differ statistically by gender for alternative loan default definitions. Except for the results of the log-rank test statistic for group loans, which is statistically significant at the 10 percent level, all remaining test statistics are statistically significant at the 1 percent level.

group loans using survival analysis during the pre- and post-COVID-19 health crisis. We report a number of noteworthy findings. Specifically, our unconditional time to default estimates suggest that female borrowers of group loans default on average 16 days earlier than male borrowers. The estimates for the conditional accelerated failure time model suggest that credit risk differs significantly by gender. A negative statistically significant coefficient for gender suggests an increase in credit risk for loans granted to female groups. This means that the time difference for group loans is meaningful from an economic point of view. The COVID-19 period materialized as a health shock that worsened repayment rates irrespective of the borrower's gender. Industry factors such as the aggregate loan default rate for the banking sector exerted the strongest impact compared with micro- and macroeconomic factors. In addition, the gender effect on the time to repay is as relevant as the impact of the loan's interest rate. Interaction effects related to gender should be incorporated in bank's loan loss reserve models or in regulatory models. Forward-looking macroeconomic variables such as consumer's confidence index and remittances should be considered as common control factors. The hazard decomposition results based on aggregate data suggest that compositional differences between male and female default rates dominate compared with covariate effects.

While we have shown the robustness of our findings across different microfinance loan default definitions, we acknowledge that our results may vary compared with other studies in other emerging or advanced economies. Moreover, factors related to the degree of discrimination in financial access and institutional development that vary across countries may intensify or exacerbate differences. It seems that it is worth exploring survival analysis techniques in other countries with a focus on understanding the time it takes borrowers to repay their loans. This seems to be a very interesting topic for future research, especially for emerging markets and even beyond.

The policy recommendation based on our study is that it is desirable to perform field studies in Mexico to investigate additional determinants or triggers of strategic default that could affect the time to repay microfinance group loans in females. International organizations could co-fund these projects.

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Internet Appendix

Appendix A

This appendix provides a discussion of i) definition of microfinance loan defaults, ii) descriptive statistics, and iii) correlation analysis. We also provide a summary content list of eight Tables and two Figures included in this appendix. To simplify our presentation, we start with the discussion of the three items and present the Tables and Figures at the end of this section. This means that a few Tables may not necessarily appear in order.

Table A1	Number of loans obtained by random sampling for each period per gender
Table A2	Variable definitions
Table A3	Mean and median survival times for micro group loans
Table A4	Tests to compare survival curves by gender
Table A5	Supplementary descriptive statistics of group loans for the dependent variable based on alternative default definitions
Table A6	Descriptive statistics
Table A7	Supplementary descriptive statistics for macroeconomic control variables
Table A8	Correlation matrix for group loans
Figure A1	Kaplan-Meier survival function for group loans by gender and “30-days past due”
Figure A2	Kaplan-Meier survival function for group loans by gender and “90-days past due”

i) Definition of microfinance loan default

The Basel II accord has defined how to measure default for large international banks at the global level for all areas exposed to credit risk. Currently, the accord is based on a standard definition of loan default that uses a “90 days past due” criterion. National supervisors have the discretion of increasing this limit up to “180 days past due.” The delinquency level used across countries varies, and occasionally it differs even between different institutions located in the same country (e.g., Bhatt & Tang, 2002; Siddiqi, 2017, p. 122). In practice, most banks structure traditional firms, mortgages, and consumer loan repayments such that the payment is made on monthly basis.⁴² Thus, the default criterion of Basel II is based on a delinquency component wherein at least three consecutive missed payments define the loan default.

ii) Descriptive statistics

Description of the full sample for the dependent⁴³ and independent micro variables is presented in Table A6, disaggregated by gender using the default definition described in Section 3.1. In our analysis, we have included reference to international data that serves as a reference and provides a valuable benchmark.

The average value of the loan’s time to default is 93 days for group loans. To the best of our knowledge, there is no data on this statistic for the microfinance sector at the global level.

As expected, the value of the average loan size is 13K in MXN for group loans. According to international data (Conning and Morduch, 2011), the average loan size value of micro loans granted by banks is 2,363 USD (i.e., around 47K in MXN), whereas the corresponding value for loans granted by non-bank financial intermediaries (NBFI) is 603 USD (i.e., around 12K in MXN). Hence, the average microfinance loan size value of Mexican banks is similar to the amount granted by NBFI. According to Karlan and Zinman (2008), longer maturity loans are preferred by microfinance borrowers as this means a

⁴² We refer specifically to non-financial private loans and exclude all bank loans to the public sector (e.g., sovereign or sub-sovereign entities) or to other financial intermediaries from this category.

⁴³ Table A5 in Appendix A provides supplementary descriptive statistics of group loans for the dependent variable based on alternative default definitions.

lower cut from their budget and consumption. In fact, Karlan and Zinman (2008) find that borrowing is more sensitive to term to maturity compared with interest rates.

The mean value of the real interest rate of group loans is 84 percent. International data show that Mexican interest rates are very high compared with countries characterized by successful and deep microcredit markets (e.g., Bangladesh, Bolivia, India, and Indonesia), where interest rates are usually lower than 30 percent per year (Banerjee, 2013, p. 488). In this regard, Mexican MFIs in our sample charge rates more similar in nature to those registered by international moneylenders for the same household, which oscillate around 60 percent per year (Banerjee, 2013, p. 488). Surprisingly, Mexican interest rates are not the highest. According to international data (Karlan and Zinman, 2010), MFIs in South Africa may charge individual loan micro interest rates as high as 200 percent APR (around 11 percent per month), whereas Banerjee (2003) documents that moneylenders may charge unimaginable expensive rates such as 5 percent per day and above.

As expected, the mean value of aggregate calendar loan default rates depends on the estimator used for group loans. The value of the loan default rate estimator for group loans is 8.25 percent for $CLDR_k$ and 7.39 percent for $CLDRO_k$. Two points are relevant at this stage. First, according to international data (Banerjee, 2013, p. 488), default rates are usually below 10 percent, and in some countries, levels often fall below 2 percent, suggesting that the Mexican default rate level for group loans is of a similar magnitude as international values. Second, Banerjee (2013) concludes that there is no clear-cut empirical data suggesting that the nature of liability present in group loans matters for repayment.

According to our sample statistics, each group loan has an average number of almost 12 borrowers. It is difficult to assess whether this number of borrowers is optimal as relevant data are not available in the literature. However, some studies have highlighted the importance of group composition. There is evidence that groups with a greater share of family members are associated with higher default rates (Ahlin and Townsend, 2007; Sharma and Zeller, 1997). Unfortunately, we do not have access to the specific borrowers' characteristics within the group. We only have information on an individual borrower that represents the group.

Our sample statistics show that the share of female loans is almost three times the male's share (75%).⁴⁴ International data suggest that approximately 50 percent of microfinance bank borrowers are women, whereas a higher share of 60 and 80 percent is registered for NBFIs and NGOs (Conning and Morduch, 2011, p.414). The share of loans granted to single obligors is high for group loans (62%). Family members may play a supporting role in terms of repayment, but this can also be the source of leverage and increased demand for resources. Unfortunately, we do not know the size of the family. In this regard, a husband may assist with the loan repayment (e.g., sending remittances), but it is also likely that the husband exerts pressure or abuses the wife to obtain resources without repayment. There is evidence that women have had to protect their savings from their husbands (Anderson and Baland, 2002).

Overall, the steady state (i.e., long-term average) statistics include a mean value for the time to default of 93 days, loan size of 13K in MXN, term to maturity of 2.16, which is approximately 98 days, borrower's age of 40 years, and restructuring rate of 7 percent. Group loans have a mean value of real interest rate of 83.7 percent and marital status of 62 percent. The analysis of the minimum and maximum values per variable suggests that there are no extreme values that may exert an influence on the estimation process.

A closer inspection of the sample characteristics by gender reveals that females are more reliable than males. In fact, an average steady-state comparison shows that group loans to females have a smaller real interest rate (79%, 98%), a greater loan size (13K, 10K),⁴⁵ a greater number of members in each group (13, 7), a smaller term to maturity (1.97, which is approximately 98 days, and 2.78, which is approximately 110 days), and a smaller aggregate loan default rate irrespective of the estimator under consideration (8.04%, 8.92% for $CLDR_k$ and 6.92%, 8.79% for $CLDRO_k$). Female group loans are similar to male group loans in terms of the fraction of restructured loans (6.91%, 7.88%), age (40.26 years, 40.66 years), and marital status (60.85%, 64.35%).

⁴⁴ In Mexico, the share of female microfinance loans for group loans is 90 percent. Our pseudo-random sample has a lower share of female loans because it is preferable to have a higher proportion of male defaults for statistical representativeness purposes.

⁴⁵ Our descriptive statistics are similar to ProDesarrollo (2021), which reports that the average value of loan size is 10.6K for group loans.

Table A6. Descriptive statistics of group microfinance loans

Variable [Units]	Sample	Obs	Mean	Std. Dev.	Min	Max
1	2	3	4	5	6	7
Time to default	FS	198058	93.52	40.42	1	599
[days]	F	150453	86.57	35.48	1	578
(TtD_PF _{j,k})	M	47605	115.47	46.74	1	599
Gender	FS	198058	75.96	42.73	0	100
[unit free]	F	150453	100	0	100	100
(G _j)	M	47605	0	0	0	0
Real interest rate	FS	198058	83.67	17.59	19.28	115.85
[%]	F	150453	78.97	16.61	19.28	115.85
(IR _{j,k})	M	47605	98.51	10.57	52.42	115.85
Term to maturity	FS	198058	2.16	1.08	1	4
[unit free]	F	150453	1.97	1.01	1	4
(M _{j,k})	M	47605	2.78	1.05	1	4
Loan size	FS	198058	12.77	11.79	0.39	156.76
[thousand peso]	F	150453	13.52	12.55	0.39	72.40
(S _j)	M	47605	10.40	8.55	1.31	156.76
Group size	FS	198058	11.58	5.63	2	50
[unit free]	F	150453	12.88	5.71	2	50
(GS _j)	M	47605	7.48	2.54	2	31
Restructured	FS	198058	7.14	25.75	0	100
[unit free]	F	150453	6.91	25.36	0	100
(Re _{j,k})	M	47605	7.88	26.94	0	100
Age	FS	198058	40.36	13.34	18	74
[years]	F	150453	40.26	13.30	18	74
(Age _{j,k})	M	47605	40.66	13.43	18	74
Marital status	FS	198058	61.69	48.61	0	100
[unit free]	F	150453	60.85	48.81	0	100
(MS _j)	M	47605	64.35	47.90	0	100
Cumulative loan	FS	198058	8.25	4.02	2.29	18.93
default rate	F	150453	8.04	4.18	2.29	18.93
[%]						
(CLDR _k)	M	47605	8.92	3.40	2.29	18.93
Cumulative loan	FS	184529	7.39	5.03	0.29	24.58
default rate by loan	F	138484	6.92	4.91	0.29	24.58
origination						
[%]						
(CLDRO _k)	M	46045	8.79	5.12	0.29	24.58

Source: Banco de México, authors' calculations.

Notes: This table reports the descriptive statistics of microeconomic variables (i.e., borrower and loan characteristics) for all group microfinance loans for the analysis period from August 2017 to

August 2021, following the default definition discussed in Section 3.1. The second column shows the statistics for: (i) Full Sample (FS), (ii) Female Sample (F), and (iii) Male Sample (M). To compute descriptive statistics, we used values of the time to default for the first record for each loan for all of the variables except in the case of restructured loans, where the last record was used due to the definition of the variable. This is because there are multiple records for each loan, and this implies that we cannot use population mean time to default (Cleves et al., 2010, pp. 91–92). Censoring implies that the estimate of our mean in Table A6 for the time to default is downward biased. Cleves et al. (2010, p.92) shows that it is not possible to estimate the mean or median survival time using standard non-survival calculations with censored observations. Among the microeconomic variables, interest rate, term to maturity, restructured, and age are time-varying. All other variables are time constant, and their value is determined at the time of loan origination. A full description of each variable is available in Table A2 in Appendix A.

Table A7 shows descriptive statistics for macroeconomic variables. Macroeconomic variables are measured in annual change (i.e., year over year). Workers' remittances grew at an annual average rate around 13 percent in our sample period, which suggests that foreign financial aid has consistently led to an increase in consumption abroad. In contrast, the average annual change in consumer confidence increased at a rate of 4.4 percent during the sample period, which suggests that the downturn in economic state did not affect the consumer's degree of optimism in the overall state of the economy. In this study, we do not use the inflation rate as a macroeconomic control variable. This is because we compute the real interest rate for each loan irrespective of its type.

iii) Correlation Analysis

The correlation matrices among microeconomic variables in Table A8 in Appendix A show the Pearson pairwise correlation coefficient. An issue that is relevant in any panel-data study is to identify whether multicollinearity is severe. As a rule of thumb, a pairwise correlation (ρ) of more than 0.70 in absolute value suggests that there is a severe problem of multicollinearity between any pair of explanatory variables, whereas for moderate correlation, it is lower than 0.70 in absolute value and higher than 0.5 in absolute value.

There is a slightly strong correlation identified for group loans between $CLDRO_k$ and COVID-19 (i.e., $\rho = -0.65$). Surprisingly, the correlation between the two estimators for calendar aggregate loan default rates is small (i.e., $\rho = 0.31$). This result suggests that these two estimators may lead to different effects on the loan performance.

The effects of collinearity are serious and well-documented in linear regression analysis. In essence, this problem may lead to coefficient estimates with the wrong sign or implausible magnitudes, high standard errors and low significance levels, and wrong fitted values and predictions. There are three possible ways to solve this problem: (i) exclude or drop predictor variables, (ii) use ridge regression, (iii) and use principal components regression.

Table A7. Descriptive statistics for macroeconomic variables

Variable	Obs	Mean	Std. Dev.	Min	Q10	Q25	Q50	Q75	Q90	Max
<i>Macroeconomic Variables (YoY)</i>										
Workers' remittances (WRem _k)	25	12.87	9.15	−2.04	4.28	6.15	10.38	17.02	26.03	39.14
Consumer confidence index (CC _k)	25	4.41	18.79	−29.32	−19.82	−9.61	2.34	17.66	31.82	39.45

Source: The National Institute of Statistics and Geography.

Notes: This table reports the descriptive statistics of the macroeconomic variables for the analysis period August 2017–August 2021. Macroeconomic variables are measured in annual change.

Table A8. Correlation matrix for microfinance-group loans

Variable		1	2	3	4	5	6	7	8	9	10	11
Gender (G_j)	1	1										
Real interest rate ($IR_{j,k}$)	2	−0.49 ^a	1									
Term to maturity (M_j)	3	−0.35 ^a	0.30 ^a	1								
Loan size (S_j)	4	0.11 ^a	−0.45 ^a	−0.07 ^a	1							
Group size (GM_j)	5	0.42 ^a	−0.54 ^a	−0.30 ^a	0.24 ^a	1						
Restructured ($Re_{j,k}$)	6	−0.01 ^a	−0.05 ^a	0.22 ^a	0.00	−0.03 ^a	1					
Age ($Age_{j,k}$)	7	−0.02 ^a	−0.20 ^a	0.01 ^a	0.15 ^a	0.01 ^a	0.01 ^a	1				
Marital status ($MS_{j,k}$)	8	−0.02 ^a	0.15 ^a	−0.00	−0.10 ^a	−0.06 ^a	0.00	−0.21 ^a	1			
Covid	9	0.23 ^a	−0.28 ^a	−0.24 ^a	0.06 ^a	0.04 ^a	0.01 ^a	0.03 ^a	0.00	1		
Consumer confidence index (CC_k)	10	−0.03 ^a	0.04 ^a	−0.12 ^a	−0.01 ^a	0.00 ^b	−0.39 ^a	−0.01 ^a	−0.00 ^a	−0.20 ^a	1	
Workers' remittances ($WRem_k$)	11	0.09 ^a	−0.09 ^a	−0.17 ^a	0.03 ^a	0.05 ^a	−0.29 ^a	0.01	−0.01	0.35 ^a	0.44 ^a	1
Cumulative loan default rate ($CLDR_k$)	12	−0.11 ^a	0.11 ^a	0.17 ^a	−0.03 ^a	−0.01 ^a	0.22 ^a	−0.02 ^a	0.01 ^a	−0.41 ^a	−0.42 ^a	−0.41 ^a
Cumulative loan default rate by loan origination ($CLDRO_k$)	13	−0.15 ^a	0.16 ^a	0.11 ^a	−0.03 ^a	−0.05 ^a	−0.17 ^a	−0.01 ^a	0.01 ^a	−0.65 ^a	0.19 ^a	−0.44 ^a
		12	13									
Cumulative loan default rate ($CLDR_k$)	12	1										
Cumulative loan default rate by loan origination ($CLDRO_k$)	13	0.31 ^a	1									

Source: Banco de México, authors' calculations.

Notes: a, (b), and [c] are significant at 1%, (5%), and [10%] level, respectively (two-sided test). This table shows the correlation matrix for group loans. Definitions of variables are in Table A2 in Appendix A.

Table A1. Number of microfinance group loans obtained by random sampling for each period per gender

Period	Women	Men	Total
ago-17	8,903	5,178	14,081
oct-17	3,985	1,666	5,651
dic-17	3,847	1,698	5,545
feb-18	3,909	1,673	5,582
abr-18	3,781	1,710	5,491
jun-18	4,091	1,671	5,762
ago-18	4,094	1,976	6,070
oct-18	4,222	1,803	6,025
dic-18	4,143	1,933	6,076
feb-19	4,102	1,944	6,046
abr-19	4,067	1,964	6,031
jun-19	4,285	1,982	6,267
ago-19	4,393	2,118	6,511
oct-19	4,368	2,238	6,606
dic-19	4,305	2,176	6,481
feb-20	4,076	2,190	6,266
abr-20	6,098	1,834	7,932
jun-20	4,226	999	5,225
ago-20	8,818	1,531	10,349
oct-20	8,109	1,692	9,801
dic-20	11,394	1,471	12,865
feb-21	7,428	1,353	8,781
abr-21	12,150	1,644	13,794
jun-21	9,690	1,601	11,291
ago-21	11,969	1,560	13,529
Total	150,453	47,605	198,058

Source: Banco de México, authors' calculations.

Notes: This table shows the total number of loans obtained by random sampling for each period per gender. We take a pseudo-random sample without replacement of 320K loans, grouping by time period and gender. The former variable is used as a grouping variable to keep a similar percentage of loans granted during the pre-COVID-19 and post-COVID-19 with a similar distribution over all $t = 1, \dots, 25$, whereas the latter variable is used to ensure that the proportion of originated bank loans is similar between men and women.

Table A2. Variable definitions

Variables (<i>Symbol</i>) [unit of analysis]	Definition	Source (P=Proprietary)
Dependent variable		
Time to default ($T_{s,j,k}$) [Days]	Broadly, this variable is the time elapsed (i.e., measured in days) until the loan is either right-censored or defaulted. In practice, each loan observation in the data records a span during which the loan is under observation, and an outcome binary variable is also used to record whether the default is observed at the end of the span. For example, each loan record (i.e., observation) has a beginning (e.g., t_0) and an ending time (e.g., t_1). We also record the outcome (e.g., defaulted or censored) at the end of the span using a supplementary variable “default status.” All in all, we use the triplet of t_0 , t_1 , and D_j to record the history and evolution of each loan in our sample. The subscript s (i.e., $s = 1, \dots, 32$) refers to the state where the borrower lives. The subscript j refers to the j th loan in the sample. The subscript k refers to the loan observation or to the time period under analysis.	CNBV (P)
Auxiliary dependent variables		
Default status ($D_{j,k}$) [Unit free]	This is a binary indicator that takes value one if the loan has defaulted and zero otherwise (i.e., right-censored). This variable forms part of the recording needed for the dependent variable in survival data. The subscript k signals that the value of this variable may change in time for each time span from 0 (i.e., loan performs) to 1 (i.e., loan defaults). In this paper, we compute three default variables. All three variables are based on a delinquency criterion. Our main default indicator follows the principle based on the consecutive number of periods of repayment. This is based on the idea that if the borrower delays the payment for at least three consecutive periods, then the loan is in default. To compute this variable, we use the number of delays or repayment and the repayment frequency. This is the most conservative loan default definition. The second follows the standard available in the literature that focuses on micro loan default, where most studies use a “30 days past due” criterion (e.g., Beck et al., 2018, for a sample of an Albanian bank; Goedecke, 2018, for a sample of Mexican banks; Zainuddin and Yasin, 2020, for a sample of global banks; Zamore et al., 2019, for a sample of global microfinance	CNBV (P)

institutions). This definition leads to very similar results compared to the first definition. This definition can be regarded as moderate, but still conservative. The third definition follows the Basel accord convention in which the default is defined for each loan when the delinquency level is at least 90 days past due. The Basel accord definition applies to a broad number of loan categories. It is often the case that regulators relax this definition to 180 days past due for a few loan types (e.g., retail loans secured by real estate, mortgage loans, and loans to public sector entities). Usually, most loans are paid on a monthly basis. Thus, the Basel accord definition implies that a loan is in default when the loan repayment is delayed for at least three consecutive periods.

Number of days of delay of repayments ($ND_{j,k}$) [days]	This is a loan-specific-time-varying variable that takes an integer positive number including zero to reflect the loan's number of days past due. This variable is used to define both the "30-day past due" and "90-day past due" default indicators.	CNBV (P)
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Repayment frequency	This is a loan-specific-time-invariant categorical variable that takes the following four values: 1 if the loan is repaid every 7 days, 2 if the loan is repaid every 10 days, 3 if the loan is repaid every 15 days, and 4 if the loan is repaid every 30 days. This variable and the number of days of delay of repayments are used to construct the main default indicator of this paper.	CNBV (P)
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Exogenous Variables

Loan characteristics

Loan size (S_j) [MXN pesos]	Size of the loan at the time of loan origination.	CNBV (P)
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Real interest rate ($IR_{j,k}$) [Percent]	This is a loan-specific-time-varying variable that defines the value of the annual interest rate of the loan minus the value of annual inflation rate in Mexico. The inflation rate is computed using the Mexican national consumer price index which is published by INEGI.	CNBV (P) and INEGI
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Term to maturity (M_j) [Unit free]	This is a categorical variable. The value of this variable depends on the number of days starting from the date that the loan originated or was restructured until maturity or exit date. This is an integer positive number that takes four possible values depending on the value of the loan's term to maturity as follows: value 1 for the first quartile (i.e., loan with a value for M_i of 1 and 78 days for group loans),	CNBV (P)
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	value 2 for the second quartile (i.e., loan with a value of M_i of 78–98 days for group loans), value 3 for the third quartile (i.e., loan with a value of M_i of 9–127 days for group loans), and value 4 for the fourth quartile (i.e., loan with a value of M_i of greater than 127 days).	
Group size (GM_j) [unit free]	Number of borrowers that form part of the loan group at the time of loan origination.	CNBV (P)
Restructured ($RE_{j,k}$) [Unit free]	This is a binary variable that takes value one if the loan is restructured and zero otherwise.	CNBV (P)
<i>Borrower characteristics</i>		
Gender (G_j) [Unit free]	This is a binary variable that takes value one if the borrower is female and zero otherwise.	Banxico (P)
Age ($Age_{j,k}$) [Date]	This is a positive time-varying continuous variable that provides the borrower's age. The months and days are included as a fraction of a calendar year that consists of 365 days (e.g., if age is 21.5, then the borrower is 21 and a half years old).	Banxico (P)
Marital status ($MS_{j,k}$) [Unit free]	This is a binary time-varying variable that takes value one if the loan borrower is single and zero otherwise.	Banxico (P)
State (s)	This is a categorical variable ($s=1,\dots,32$) that may take 1 out of 32 integer values for the borrower's address state location at the time of loan origination.	Banxico (P)
<i>Aggregate default rate indicators</i>		
Cumulative loan default rate ($CLDR_k$) [Percent]	This is a default rate measure based on the calendar time of the reported data. The indicator is the sum of the total loans that default in the period over the total number of loans for each bimester.	CNBV (P)
Cumulative loan default rate by loan origination ($CLDRO_k$) [Percent]	This is a default rate measure based on the calendar time of the reported data at the time of loan origination. The numerator is the sum of loan defaults for the loan's originated in time t over the total number of loans originated in time t .	CNBV (P)
<i>Macroeconomic variables</i>		
Workers' remittances ($WRem_k$) [Millions of dollars]	Total workers' remittances. Workers' remittances can be decomposed as money orders, personal checks, electronic transfers, and remittances in kind and cash. The large majority of workers' remittances arrives through electronic transfers.	Banxico
Consumer confidence	Consumer confidence indicator is available on a monthly basis. The value of this	INEGI

index (CC_k)
[Unit free]

index is obtained as an average of five variables that describe the actual and expected economic Mexican households' expectations. This series is seasonally adjusted.

Source: Banco de México (Banxico, its acronym in Spanish), National Institute of Statistics and Geography (INEGI, its acronym in Spanish), National Banking and Securities Commission (CNBV, its acronym in Spanish). We use P to differentiate proprietary from publicly available data.

Notes 1: This table lists the set of dependent and exogenous variables, along with their respective symbol and definition, which we use to fit the standard survival models. The last column lists the source of our data, where CNBV is the acronym in Spanish for the National Banking and Securities Commission, INEGI is the acronym in Spanish for the National Institute of Statistics and Geography, and Banxico is the acronym in Spanish for the Central Bank of Mexico. Loan and borrower characteristics are available at a bimonthly frequency. The reporting frequency for all macroeconomic variables is monthly.

Notes 2: The relationship between analysis time and calendar time can be described as follows:

$$t = \frac{\text{time} - \text{origin}}{\text{scale}}$$

where t is analysis time, “time” refers to calendar time, origin is a date of reference, and scale is used to express t in alternative units (i.e., days, month, year). For all loans in our sample, we have the origination date. Some loans were originated outside our sample period. It is convenient to use the date when the loan was originated for “origin,” whereas scale is fixed at value 1 and analysis time t is measured in days. We could set scale value to 30 to express t in months, but days is our preferred unit choice. Hence, analysis time is 0 for the date when the loan was originated (i.e., the onset of risk). In other words, analysis time is measured at the loan level as the number of days elapsed from its origination until either default or censored occurs. For each loan, we have multiple loan records (i.e., time span). STATA generates four variables after using STSET: $_t0$ and $_t_d$, and $_st$. The first two variables record the time span in analysis time units for each loan record (i.e., observation). Each record starts at $_t0$ and concludes at $_t$. Variable $_d$ is binary indicator, and it takes value one if the loan defaults and zero otherwise. Variable $_st$ records whether the observation contributes to the current analysis. We do not use $_st$ in this study. The onset of risk is well defined in loan data such that it is easy to define $t = 0$ for all loans and let t increase at the loan level in integer values from 1 up to the last recorded date available in the sample based on calendar time. So, analysis time measures the time to default in integer values measured in days. Our first two default rate measures are based on analysis time, and these consider aggregate past default times and censoring time (i.e., default has not occurred during the observed sample window), and our third default time is based on calendar time and considers the default rate for the period reported.

Table A3. Mean and median survival times for microfinance group loans

Default definition	Gender	Number of Subjects	Median	Standard Error	[95% Conf. Interval]		Restricted Mean	Standard Error	[95% Conf. Interval]	
Payment Frequency	Male	48K	201	1.02	199	202	206.06(*)	0.64	204.81	207.31
	Female	150K	185	0.45	184	185	191.93(*)	0.63	190.69	193.16
	All	198K	192	0.50	190	193	199.10(*)	0.45	198.22	199.98
30 days past due	Male	48K	190	0.70	189	192	197.71(*)	0.64	196.45	198.97
	Female	150K	184	0.43	184	185	193.18(*)	0.69	191.82	194.54
	All	198K	187	0.35	186	188	195.70(*)	0.47	194.77	196.62
90 days past due	Male	48K	283	2.64	277	290	289.14(*)	5.51	278.34	299.95
	Female	150K	307	6.01	297	322	334.09(*)	13.93	306.77	361.40
	All	198K	292	2.81	287	298	303.88(*)	5.93	292.26	315.51

Source: Banco de México, authors' calculations.

Notes: This table reports the estimated mean and median survival times by gender and for the full sample for bank microfinance loans to group borrowers for the analysis period from August 2017 to August 2021, following three alternative default definition discussed in Section 3.1. A (*) indicates that the largest observed analysis time is censored; therefore, the mean is underestimated. The median survival time $t_{50} = \mu_T$ is the time beyond which 50 percent of loans are expected to survive (i.e., $S(\mu_T) = 0.5$). We use the function `stci` by gender in STATA to obtain the mean and median survival time. See Cleves et al. (2010, p.118) for details on the formula used to compute the large-sample standard errors. In practice, the median survival time is preferred over the mean, because the latter tends to be right-skewed. The estimated mean is referred as restricted mean. This is because the estimator based on the Kaplan Meier is not available beyond the largest observed default time. As a result, a restricted mean underestimates the true mean when the last observed time to default time is censored. Standard error and confidence interval estimates correspond to the restricted mean.

Table A4. Tests to compare microfinance loan survival curves by gender for group borrowers

Test	Default Definition	Gender	Events Observed	Events Expected	Total	Sum of Ranks	Chi ² (1)	Pr > Chi ²
Log-rank Test	Payment	Men	6,925	7,866	15,019	-	249	0.0000
	Frequency	Women	8,094	7,153	15,019	-		
	30 days	Men	6,992	7,097	14,153	-	3	0.0716
	past due	Women	7,161	7,056	14,153	-		
	90 days	Men	1,454	1,155	2,059	-	185	0.0000
	past due	Women	605	904	2,059	-		
Wilcoxon Test	Payment	Men	6,925	7,866	15,019	7,806,950	7	0.0080
	Frequency	Women	8,094	7,153	15,019	-7,806,950		
	30 days	Men	6,992	7,097	14,153	46,819,058	248	0.0000
	past due	Women	7,161	7,056	14,153	-46,819,058		
	90 days	Men	1,454	1,155	2,059	14,996,667	334	0.0000
	past due	Women	605	904	2,059	-14,996,667		
Tarone-Ware Test	Payment	Men	6,925	7,866	15,019	-77,528	61	0.0000
	Frequency	Women	8,094	7,153	15,019	77,528		
	30 days	Men	6,992	7,097	14,153	79,009	65	0.0000
	past due	Women	7,161	7,056	14,153	-79,009		
	90 days	Men	1,454	1,155	2,059	50,870	281	0.0000
	past due	Women	605	904	2,059	-50,870		

Source: Banco de México, authors' calculations.

Notes: This table shows three test results for three alternative default definitions to compare survival experience by gender between bank microfinance loans to group borrowers using formal tests of hypothesis. The null hypothesis is that the two survival curves are equal. Since the relative survival experience of the bank loans may be characterized by the groups' hazard functions, the null hypothesis can be expressed in the hazards as $H_0: h_{\text{Female}}(t) = h_{\text{Male}}(t)$. Essentially, these are global tests that compare the overall survivor functions. These tests compare at each default time the expected versus the observed number of loan defaults for each group and combine these comparisons over all observed loan default times. Each test is different only with respect to how they weight each of the individual comparisons that occur at each default time to form one overall test statistic. It is important to point out that these tests do not test the equality of the survivor functions at a specific point in time.

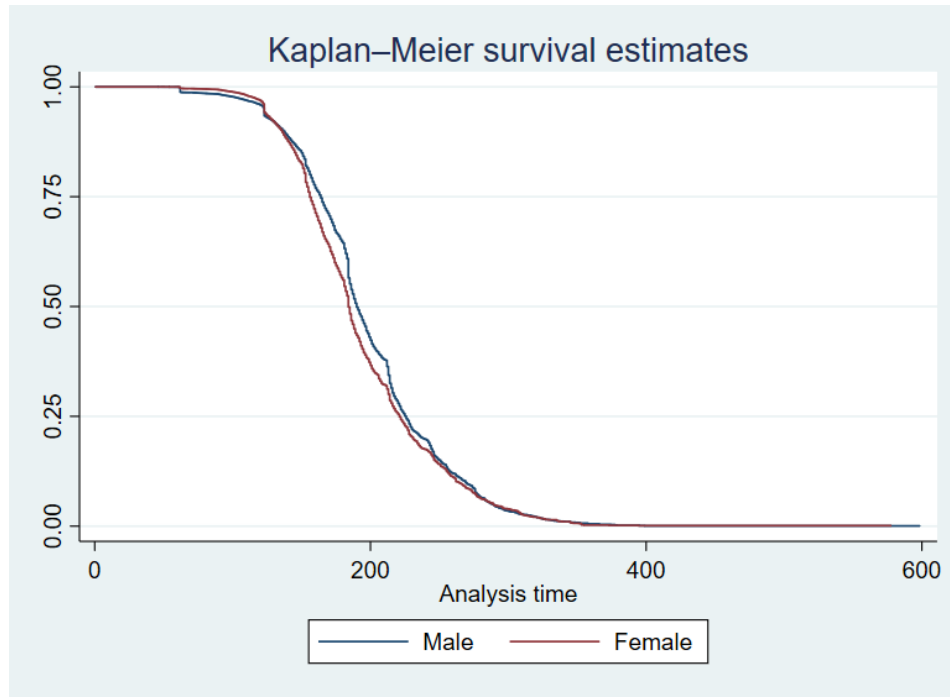
Table A5. Supplementary descriptive statistics of microfinance loans group borrowers for the dependent variable based on alternative default definitions

Variable	Sample	Obs	Mean	Std. Dev.	Min	Max
Time to default [days] (TtD_PF _{j,k})	FS	198058	93.52	40.42	1	599
	F	150453	86.57	35.48	1	578
	M	47605	115.47	46.74	1	599
Time to default [days] (TtD_30D _{j,k})	FS	198058	92.30	38.43	1	599
	F	150453	86.08	34.54	1	578
	M	47605	112.47	43.21	1	599
Time to default [days] (TtD_90D _{j,k})	FS	198058	93.52	40.42	1	599
	F	150453	86.57	35.48	1	578
	M	47605	115.47	46.74	1	599
Default rate based on Payment frequency [%] (D_PF _k)	FS	198058	7.58	26.47	0	1
	F	150453	5.38	22.56	0	1
	M	47605	14.55	35.25	0	1
Default rate 30 days [%] (D_30D _k)	FS	198058	7.14	25.76	0	1
	F	150453	4.76	21.29	0	1
	M	47605	14.68	35.39	0	1
Default rate 90 days [%] (D_90D _k)	FS	198058	1.04	10.14	0	1
	F	150453	0.40	6.33	0	1
	M	47605	3.05	17.21	0	1

Source: Banco de México, authors' calculations.

Notes: This table reports supplementary descriptive statistics for dependent variables (i.e., time to default, default rate) for all group microfinance loans by gender for the analysis period from August 2017 to August 2021. The time to default is computed based on alternative default definitions discussed in Section 3.1. To compute descriptive statistics, we used values of the time to default for the last record for each loan. This is because there are multiple records for each loan, and this implies that we cannot use population mean time to default (Cleves et al., 2010, pp. 91–92). Censoring implies that the estimate of our mean in Table A5 for the time to default is downward biased. Cleves et al. (2010, p. 92) shows that it is not possible to estimate the mean or median survival time using standard non-survival calculations with censored observations.

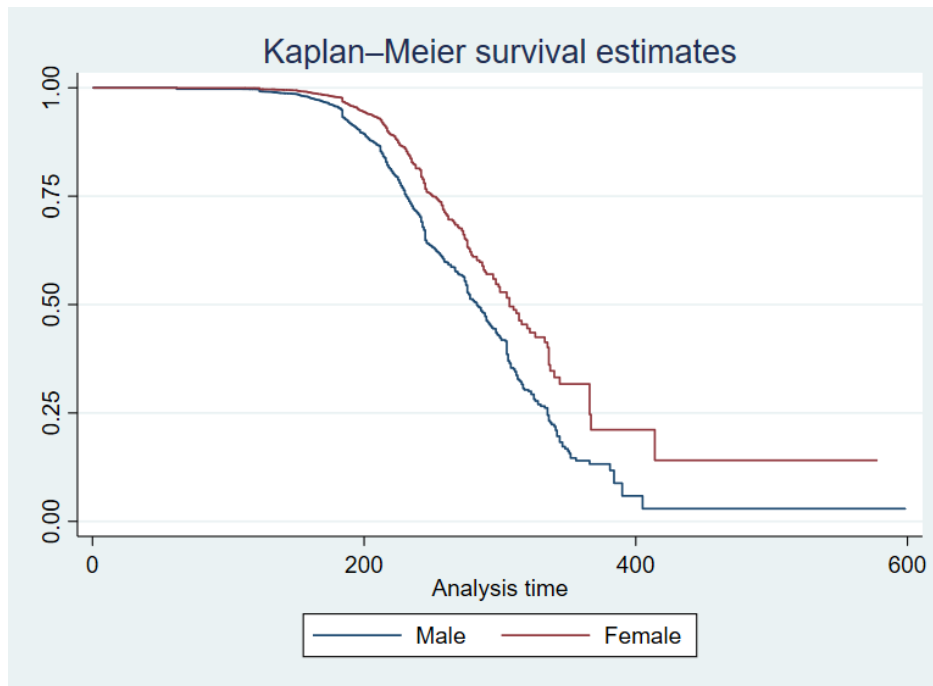
Figure A1. Kaplan-Meier survival function for microfinance group loans by gender and “30-days past due”



Source: Banco de México, authors’ calculations.

Notes: This figure reports the evolution of the estimated survivor curve using the Kaplan-Meier estimator for bank microfinance loans to groups of borrowers by gender. This graph was generated in STATA using the command “sts graph” along with the option “survival.” The Y-axis shows the survival rate in percent. Here “analysis time” represents the lifetime of group loans in days. This figure reports the estimator for bank loans to groups using the default definition based on loans that are in arrears at least for 30 days.

Figure A2. Kaplan-Meier survival function for microfinance group loans by gender and “90 days past due”



Source: Banco de México, authors' calculations.

Notes: This figure reports the evolution of the estimated survivor curve using the Kaplan-Meier estimator for bank microfinance loans to groups of borrowers by gender. This graph was generated in STATA using the command “sts graph” along with the option “survival.” The Y-axis shows the survival rate in percent. Here “analysis time” represents the lifetime of group loans in days. This figure reports the estimator for bank loans to groups using the default definition based on loans that are in arrears at least for 90 days.

Appendix B

In this appendix, we report the results of the statistical test used to justify the choice of the log-normal distribution for our AFT model as discussed in Section 4.

B.1. Choosing between non-nested parametric models

There are six parametric distributions available in STATA to fit the AFT model, which includes (i) exponential, (ii) Weibull, (iii) Gompertz, (iv) log-normal, (v) log-logistic, and (vi) generalized gamma. Although the most flexible modeling parametric choice is the generalized gamma, we experienced severe convergence problems, and hence, we omitted this distribution from our analysis and focused on the remaining five parametric distributions. To determine the appropriate distribution for our data, we use the AIC test criteria.⁴⁶ For non-nested models, the preferred model is the one with the lowest AIC. Table B1 shows the log likelihoods and AIC values for microfinance group loans. Based on the AIC criterion, the lognormal is the best model for the micro group loan data.

Table B1. Assessing parametric distribution fit using Akaike Information Criterion for group loans

Distribution	Log-Likelihood	Covariates ^a	Parameters ^b	AIC
Exponential	-36,075.09	8	1	72,280.17
Weibull	-8,903.39	8	2	17,938.78
Gompertz	-16,988.40	8	2	34,108.79
Lognormal	-5,685.03	8	2	11,502.06
Loglogistic	-5,935.88	8	2	12,003.75

Source: Banco de México, authors' calculations.

Notes: (a) This is the number of model covariates excluding the intercept term; (b) this is the number of model-specific distributional parameters. This table presents the Akaike Information Criterion (AIC), which is used to discriminate between different parametric distributions in the context of non-nested models for group loans. The standard AFT model that we use for testing the distribution parametric fit corresponds to the baseline model that includes loan and borrower characteristics as described in eq.(1) and discussed in Section 4.2. The preferred model or the model that provides the best fit is the one with the lowest AIC. The AIC is defined as $-2\ln L + 2(k + c)$, where $\ln L$ is the log likelihoods, k is the number of model covariates excluding the intercept term, and c is the number of model-specific distributional parameters.

⁴⁶ The Akaike criterion is designed to punish each model's log likelihood to consider the number of parameters being estimated and then comparing log likelihoods.

Appendix C

In this appendix, the marginal effects for the five multiple regression tables (i.e., Tables 2 to 6) are presented.

Table C1. Marginal effects for the univariate AFT survival models for bank loans to microfinance group borrowers

Model 1	Variable 2	Marginal effect (Unit increase in x)		Auxiliary parameters	
		1-sigma 3	1-unit 4	Beta 5	Std. Dev 6
M1: Gender _j	Gender	0.9825	0.9595	−0.0413 ^a	0.4273
M2: M1 + State FE	Gender	0.9845	0.9641	−0.0365 ^a	0.4273
M3: M2 + Time FE	Gender	0.9688	0.9285	−0.0742 ^a	0.4273
M4: M3 + Covid	Gender	0.9755	0.9435	−0.0581 ^a	0.4273
M4: M3 + Covid	Covid	0.8716	0.7569	−0.2785 ^a	0.4935
M4: M3 + Covid	Gender*covid	0.8666		−0.0116	

Source: Banco de México, authors' calculations.

Notes: a, (b), and [c] are significant at 1%, (5%), and [10%] level, respectively (two-sided test). This table displays the marginal effects for the univariate estimated survival model for bank microfinance loans to group borrowers. Survival time univariate regression results of eq.(1): $\ln(t_{jk}) = \beta_0 + \beta_1 x_{1jk} + \dots + \beta_p x_{pjk} + \ln(\tau_{jk})$, correspond to the univariate model of Table 2. Column (1) defines the model under analysis. Our models are nested. Column (2) defines the variable under analysis. Columns (3) and (4) show the marginal effect has been computed for both a σ -unit increase and a 1-unit increase in exogenous variable (x) following eq.(3), which describes exponentiated coefficients interpreted as time ratios. The σ -unit increase is computed as $\exp(\beta_x \sigma_x)$ for non-interacted variables and $\exp(\beta_x \sigma_x + \beta_{int} \sigma_x)$ to include the effect of interaction terms, where β_{int} is the coefficient of the interacted variable. In turn, the 1-unit increase is computed as $\exp(\beta_x)$ for non-interacted variables or $\exp(\beta_x + \beta_{int})$ to include the effect of interaction terms. A 1-unit increase in gender is approximately 2.5 times the size of the standard deviation. For reference purposes, Column (5) shows the estimated coefficient, whereas Column (6) shows the size of the standard deviation (σ) of gender (x_j) as described in Table A6.

Table C2. Marginal effects for the multivariate AFT survival models for bank loans to microfinance group borrowers

Variable	Marginal effect (Unit increase in x)		Auxiliary parameters	
	1-sigma	1-unit	Beta	Std. Dev
1	2	3	4	5
Gender _j	0.9799	0.9537	−0.0474 ^a	0.4273
Real interest rate _{jk}	0.9923	0.9996	−0.0442 ^a	0.1750
TtM _j = 2	1.2796	1.2461	0.2200 ^a	1.1204
TtM _j = 3	1.4857	1.4238	0.3533 ^a	1.1204
TtM _j = 4	1.8269	1.7123	0.5378 ^a	1.1204
Loan size _j	1.0087	1.0010	0.0133 ^a	0.6650
Group size _j	0.9977	0.9996	−0.0004 ^a	5.6287
Restructured _j	1.0486	1.2022	0.1842 ^a	0.2575
Age _j	1.0119	1.0009	0.0009 ^a	13.3361
Marital status _j	0.9890	0.9776	−0.0227 ^a	0.4861
Covid	0.9131	0.8318	−0.1842 ^a	0.4935

Source: Banco de México, authors' calculations.

Notes: a, (b), and [c] are significant at 1%, (5%), and [10%] level, respectively (two-sided test). This table displays the marginal effects for the multivariate estimated survival model for bank loans to micro group loans using micro (i.e., borrowers and loan characteristics) variables. Survival time multivariate regression results of eq.(1) $\ln(t_{jk}) = \beta_0 + \beta_1 x_{1jk} + \ln(\tau_{jk})$, correspond to the multivariate model of Table 3. For reference purposes, column (3) shows the estimated coefficient, whereas column (4) shows the size of the standard deviation (σ) of the borrowers and loan characteristics as described in Table A6. The marginal effect has been computed for both a σ -unit increase (i.e., $\exp(\beta_1 \sigma)$) and a 1-unit increase $\exp(\beta_1)$ in each variable (x) following eq.(3), which describes exponentiated coefficients interpreted as time ratios.

Table C3. Marginal effects for the multivariate AFT survival models for bank loans to microfinance group borrowers

Variable 1	Marginal Effect (Unit increase in x)		Auxiliary Parameters	
	1-sigma 2	1-unit 3	Beta 4	Std. Dev 5
Real interest rate _{jk} *gender _j	0.9965	0.9998	0.1160 ^a	0.1750
TtM _j = 2*gender _j	1.2788	1.2455	−0.0499 ^a	1.1204
TtM _j = 3*gender _j	1.4682	1.4089	−0.1032 ^a	1.1204
TtM _j = 4*gender _j	1.7597	1.6560	−0.1580 ^a	1.1204
Loan size _j *gender _j	1.0086	1.0132	−0.0005	0.6650
Restructured _j *gender _j	1.0591	1.2498	0.0550 ^a	0.2575
Age _j *gender _j	1.0095	1.0007	−0.0005 ^a	13.3361
Marital status _j *gender _j	0.9881	0.9756	−0.0032	0.4861
Covid *gender _j	0.8966	0.8016	−0.0213 ^a	0.4935

Source: Banco de México, authors' calculations.

Notes: a, (b), and [c] are significant at 1%, (5%), and [10%] level, respectively (two-sided test). This table displays the marginal effects for the multivariate estimated survival model for bank loans to micro group loans using micro (i.e., borrowers and loan characteristics) variables. Survival time multivariate regression results of eq.(1): $\ln(t_{jk}) = \beta_0 + \beta_1 x_{1,jk} + \ln(\tau_{jk})$, correspond to the multivariate model of Table 4. For reference purposes, Column 3 shows the estimated coefficient, whereas Column 4 shows the size of the standard deviation (σ) of the borrowers and loan characteristics as described in Table A6. The marginal effect has been computed for both a σ -unit increase (i.e., $\exp(\beta_1 \sigma)$) and a 1-unit increase $\exp(\beta_1)$ in each variable (x) following eq.(3). which describes exponentiated coefficients interpreted as time ratios.

Table C4. Marginal effects for the multivariate AFT survival models for bank loans to microfinance group borrowers

Variable 1	Marginal effect (Unit increase in x)		Auxiliary parameters	
	1-sigma 2	1-unit 3	Beta 4	Std. Dev 5
$CLDR_{k-l}$	0.8028	0.9135	-5.4312 ^a	0.0402
$CLDR_{k-l} * \text{Gender}_j$	0.8138	0.9181	0.3090 ^a	0.0402
$CLDRO_{k-l}$	0.8411	0.9463	-3.4408 ^a	0.0503
$CLDRO_{k-l} * \text{Gender}_j$	0.8464	0.9463	0.1263 ^a	0.0503

Source: Banco de México, authors' calculations.

Notes: a, (b), and [c] are significant at 1%, (5%), and [10%] level, respectively (two-sided test). This table displays the marginal effects for the multivariate estimated survival model for bank loans to microfinance group loans using the baseline model with three alternative past default rate variables (see Table A2 in Appendix A for variable definitions). Survival time multivariate regression results of eq.(1): $\ln(t_{jk}) = \beta_0 + \beta_1 x_{1jk} + \dots + \beta_p x_{pjk} + \ln(\tau_{jk})$, correspond to the multivariate model of Table 5. Columns (3) and (4) show the marginal effect has been computed for both a σ -unit increase (i.e., $\exp(\beta_x \sigma_x)$ for non-interacted variables or $\exp(\beta_x \sigma_x + \beta_{\text{int}} \sigma_x)$ to include the effect of interaction terms, where β_{int} is the coefficient of the interacted variable), and a 1-unit increase (i.e., $\exp(\beta_x)$ for non-interacted variables or $\exp(\beta_x + \beta_{\text{int}})$ to include the effect of interaction terms) in exogenous variable (x) following eq.(3), which describes exponentiated coefficients interpreted as time ratios. For reference purposes, Column (5) shows the estimated coefficient, whereas Column (6) shows the size of the standard deviation (σ) of the past default rate variables as described in Table A6.

Table C5. Marginal effects for the multivariate AFT survival models for bank microfinance loans group borrowers

Model	Variables	Marginal effect (Unit increase in x)		Auxiliary parameters	
		1-sigma	1-unit	Beta	Std. Dev
1	2	3	4	5	6
<i>CLDR_{k-1}</i>	Remittances	1.0390	1.0042	0.0042 ^a	9.1486
	Consumer confidence	0.9927	0.9996	-0.0004 ^a	18.792
<i>CLDRO_{k-1}</i>	Remittances	1.0209	1.0023	0.0023 ^a	9.1486
	Consumer confidence	1.0087	1.0005	0.0005 ^a	18.792

Source: Banco de México, authors' calculations.

Notes: a, (b), and [c] are significant at 1%, (5%), and [10%] level, respectively (two-sided test). This table displays the marginal effects for the multivariate estimated survival model for bank loans to microfinance group loans using the baseline model with five macroeconomic variables. Survival time multivariate regression results of eq(1): $\ln(t_{jk}) = \beta_0 + \beta_1 x_{1jk} + \dots + \beta_p x_{pjk} + \ln(\tau_{jk})$, correspond to the multivariate model of Table 6. Columns (3) and (4) show the marginal effect has been computed for both a σ -unit increase (i.e., $\exp(\beta_x \sigma_x)$ for non-interacted variables or $\exp(\beta_x \sigma_x + \beta_{int} \sigma_x)$ to include the effect of interaction terms, where β_{int} is the coefficient of the interacted variable) and a 1-unit increase (i.e., $\exp(\beta_x)$ for non-interacted variables or $\exp(\beta_x + \beta_{int})$ to include the effect of interaction terms) in exogenous variable (x) following eq.(3), which describes the exponentiated coefficients interpreted as time ratios. For reference purposes, Column (5) shows the estimated coefficient, whereas Column (6) shows the size of the standard deviation (σ) of the macroeconomic variables as described in Table A7.