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Contagious loan default☆

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HIGHLIGHTS

- A hazard model is applied to regulatory data on loans from Mexican banks.
- Geographical spillover effects on credit risk in group lending are estimated.
- Default rates of nearby dwellers substantially add to ex-post credit risk.

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ABSTRACT

Applying survival analysis to a large loan-level dataset for regulatory purposes on group loans provided by Mexican banks, I find that ex-post credit risk is subject to substantial geographic spillover effects. Potential underlying mechanisms include contagious defaulting behavior, which bears the risk of proliferating into a repayment crisis in the event of an economic or political shock, as experiences from similar markets suggest.

1. Introduction

Several default crises have shaken up the microfinance sector over the past decade.[1] While underlying market conditions and crisis triggers varied, a common observation was that default rates began to mount locally and eventually spread across the market. This study investigates the role of geographic spillovers in transmitting credit risk by applying a Cox regression model to a large panel dataset of group loans in Mexico from 2012 to 2017. The results confirm that geographic spillovers within a neighborhood substantially add to credit risk.

Micro-level geographic spillovers, which are typically linked to network effects, have been traced in different contexts of financial decision-making, such as stock trading behavior (Hong et al., 2005), mortgage defaults (Gupta, 2016), or bank runs (Iyer and Puri, 2012; Kiss et al., 2014). In microfinance, network effects are usually studied in the context of group lending, with a focus on a borrower's repayment behavior vis-à-vis her loan group (Cassar et al., 2007; Allen, 2016; Breza, 2012; Katzur and Lensink, 2012).[2] In contrast, no systematic evidence is available about geographic transmission of credit risk *beyond* loan groups. Banerjee et al.

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1 Most prominently in the Indian state Andhra Pradesh (Mader, 2013), Nicaragua (Servet, 2015), Bosnia and Herzegovina (Augsburg et al., 2015), and Morocco (Rozas et al., 2014), but also elsewhere.

2 In the group lending method, borrowers form a group in which every member obtains an individual loan but is liable for the repayment of the loans from all other members. It thus allows lenders to cope with credit risk by outsourcing costly monitoring efforts to the borrowers.

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(2013) observe in an Indian context that word-to-mouth information flowing between potential borrowers across villages substantially explains the uptake of microfinance products; arguably, such network effects may extend to credit risk as well. Bond and Rai (2009) show theoretically how strategic defaults can contaminate the entire market when borrowers, observing each others' actions, expect the repayment performance of other borrowers to deteriorate.

In Mexican microfinance, unlike in other Latin American countries, group lending continues to be the dominant lending method, mainly because restrictive regulations have curbed the expansion of individual microlending (WWB, 2014). Accounts of widespread over-indebtedness among borrowers raise concerns among practitioners that the market may be the next to be heading towards a default crises.[3] A case in point is Mexico's own history with "borrower runs": following a dramatic peso devaluation in 1994 that preceded an economic crisis, Mexican borrowers defaulted strategically, anticipating that loan repayment would not prevent lenders, who had already seen their asset positions plummet, from financial distress (Trautmann and Vlahu, 2013).

In the remainder of the paper, Section 2 presents the dataset and the Cox regression model, Section 3 discusses the results, and Section 4 briefly concludes.

2. Empirical setting

2.1. Data

The dataset, owned and maintained by Banco de México for regulatory purposes, covers all loans made via group lending from Mexican banks in the period from January 2012 to April 2017.[4] Regulated banks bimonthly report information on every outstanding loan to the central bank, which yields $T = 32$ time periods. Aggregated on the group level, the dataset contains nearly 10 million panel observations. The analysis is run for 32,000 randomly drawn loan groups, equally distributed over all $t = 1, \ldots, 32$ (1000 per bimester). Since each group is observed repeatedly over time, the final sample contains 80,814 observations. After discarding information from groups after they defaulted, the final sample size is 59,796. Random sampling ensures that the subsample is an independently and identically distributed sample of the population of interest, which here is composed of all borrowers from regulated banks who were part of a loan group between 2012 and 2017. Further, since the p-value of a consistent and nonzero estimate converges to zero when sample size tends to infinity, random sub-sampling alleviates the problem that small and practically insignificant effects tend do be estimated as being highly statistically significant in large samples.

2.2. Methodology

Determinants of a loan group's ex-post risk to default are estimated via Cox's proportional hazards regression model. The dependent variable is the hazard to default, which denotes the rate by which groups default on a loan for the first time, given that a period t has elapsed since group formation. To filter out cases where repayment is merely delayed for a short period, only arrears of at least 30 days qualify as defaults. Hazard models account for changes of independent variables over time and thereby outperform static methods such as a logistic regression (Shumway, 2001). Another advantage of the Cox model is that no specific probability distribution of defaults needs to be imposed, which classifies it as semiparametric estimator. Conditional on a time-dependent random vector X_t and denoting time-to-default by T, the hazard is defined as

$$\lambda(t|X_t) = \lim_{\Delta t \to 0} \frac{P(t \le T < t + \Delta t | t \le T, X_t)}{\Delta t} \tag{1}$$

Following Iyer and Puri (2012), neighborhood spillover effects are measured as the fraction of loan groups in default for at least 30 days in the neighborhood of group i at time t, where a neighborhood is proxied by postal codes. To ensure that group i's outcome does not alter the neighborhood default rate for this group, it is left out from the calculation. The "leave-one-out" neighborhood default rate is denoted by $D_{(-i)t}$. To allow for correlation among observations within a neighborhood, standard errors are clustered on the neighborhood level. Since the default of group i at time t might influence whether other loan groups in the same neighborhood default at t and thereby may cause reverse causality, the same models are run using the neighborhood default rate lagged by one bimester, denoted by $D_{(-i)t-1}$.

The models control for loan loss provisions reserved by the banks at the time of the loan disbursal, which reflect the banks' *ex-ante* perceived credit risk of borrowers (D'Espallier et al., 2011), and can be considered a function of otherwise unobserved borrower characteristics. Additional control variables are the loan's term to maturity, current maturity at time t, borrowers' loan cycles, inflation-adjusted interest rate, loan size,[5] and group size (including a squared term to account for nonlinear effects of group size, as suggested by Impavido, 1998). Those variables are determined at the beginning of each loan round and are thus not affected by the eventual loan outcome. Further, the total number of loan groups in a neighborhood at time t is included, proxying the degree of local market penetration of group loans. The control variables are stacked in the vector Z_t. Finally, regressions include the vector $\psi = (\tau, \zeta, \xi)$, denoting time, state, and bank fixed effects (indexed by t, s and b, respectively). The model elaborates to

$$\lambda(t|D_{(-i)r}, Z_{it}, \psi_{tsb}) = \lambda_0(t) \exp(\beta D_{(-i)r} + Z_{it}\delta + \tau_t + \zeta_s + \xi_b), \quad \text{for } r \in \{t, t-1\} \tag{2}$$

where $\lambda_0(t)$ is the "baseline hazard", conditional on all independent variables being zero.

3. Results

Table 1 summarizes the random sample. 3% of the observations involve a default of at least 30 days. Loans are small (9756 Mexican pesos, or less than $US 500) and have a short maturity (134 days), both of which are typical group credit features. They are expensive even for international microcredit standards (86% inflation-adjusted annual interest rate), which is peculiar to the Mexican market (Angelucci et al., 2015). Groups are on average composed of 11 members, the majority of whom are experienced borrowers that have advanced to their sixth loan cycle at the mean. The latter means that most borrowers have built a credit history, which explains the banks' relatively low average loan loss reserve ratio of 1.2% of the loan amount.

Fig. 1 shows exemplary snapshots of the geographic distributions of defaults aggregated on the municipality level in two federal states, Veracruz and Chiapas. Both states feature important microfinance markets, with Veracruz being Mexico's largest in terms of volumes and number of clients. While only illustrative, the

[3] See, for instance, https://cfi-blog.org/2017/01/09/growing-concerns-about-overindebtedness-in-mexicos-microfinance-sector/, or http://www.e-mfp.eu/blog/microfinance-mexico-beyond-brink, both accessed on March 27, 2018.

[4] Due to data confidentiality, information on the lending institutions is not disclosed.

[5] Both interest rate and loan size are averaged within a loan group, since loan terms can differ across group members.