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Artículo

Default risk in microfinance institutions: Case of a Costa Rican company with agricultural loan portfolio

Riesgo de impago en instituciones microfinancieras: El caso de una empresa costarricense con cartera crediticia agropecuaria

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Resumen

El más reciente Informe Económico del Banco Interamericano de Desarrollo posiciona a Costa Rica como el segundo país de Centroamérica con más endeudamiento de los hogares y casi la mitad de estos no mantiene ahorros. Estas condiciones han provocado incrementos en los índices de morosidad de los acreedores de préstamos. En esta investigación se analizan los factores que afectan la morosidad en una institución microfinanciera costarricense que otorga microcréditos a personas y pequeños negocios sin acceso al financiamiento bancario tradicional. Se aplicó un enfoque econométrico con datos de panel y los resultados demuestran que la morosidad se ve afectada por componentes autorregresivos y la actividad financiada. La aplicación de estas metodologías permite reforzar los análisis crediticios y la selección de nichos de mercado para mitigar el riesgo de impago.

Palabras clave: autorregresivo, econometría, datos de panel, pronóstico, endeudamiento, cultura de pago.

Abstract

The most recent Economic Report of the Inter-American Development Bank ranks Costa Rica as the second country in Central America with the highest household indebtedness, and almost half of households have no savings. These conditions have led to increases in the default rates of loan creditors. This research analyzes the factors affecting default in a Costa Rican Microfinance Institution that grants microcredits to individuals and small businesses without access to traditional bank financing. An econometric approach with panel data was applied and the results show that default is affected by autoregressive components and the financed activity. The application of these methodologies allows strengthening credit analysis and the selection of market niches to mitigate the default risk.

Key words: autoregressive, econometrics, panel data, forecast, indebtedness, payment culture.

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Introduction

Microfinance Institutions (MFIs) play an important role in developing countries´ financial markets by promoting microcredit for economic and social development in rural areas. MFIs provide loans to self-employed and micro, small and medium-sized enterprises (MIPYMES), who often have low incomes and are excluded from traditional banking because they lack audited financial statements and loan guarantees (Camacho, 2016; Estrada & Hernández, 2019; Redcamif, 2019).

The social work of MFIs is indispensable: MFIs reduce poverty, promote agriculture and food security, facilitate access to health services, foster inclusive economic growth and stimulate employment (Forbes Mexico, 2015; Tehulu, 2013). In june 2020, Costa Rican MFIs[1] reported a loan portfolio of US$37.6 million, with an average loan amount between US$366 and US$5 435, most of which was placed in rural areas (77%) and to female clients (55%) (Redcamif, 2020a).

An analysis published by the Inter-American Development Bank ranked Costa Rica as the second country in Central America with the highest household indebtedness, even though 50% of households do not have savings funds (OECD, 2020; Ruiz-Arranz et al., 2022). Likewise, since 2018, a weakening of global economic activity and a decline in business confidence were reported (IMF, 2019, 2020), which were aggravated by the increase in unemployment caused by the COVID-19 pandemic. This macroeconomic scenario affected the dynamism and quality of Central American MFIs portfolios with a 6.4% decrease in the size of their loan portfolios in the first half of 2020 (Redcamif, 2020b).

Until 2019 the portfolio quality indicator PeR>30 (Portfolio at Risk greater than 30 days) for Costa Rican MFIs remained below 7% (acceptable standard), but in 2020 it increased to 8.6% (Redcamif, 2020b). This quality loss generated a financial alarm for MFIs,

[1] In Costa Rica, MFIs do not have a legal commitment to affiliate with the networks and not all of them are supervised by the respective supervisory entity (SUGEF, 2020).

as in other financial entities (BCCR, 2019a, 2020b). Default risk is one of the main indicators that financial institutions must manage, as it can negatively affect client loyalty and lead to speculation about loan recovery (Aguilar and Camargo, 2002).

In MFIs, loan recovery is fundamental for their sustainability, since a significant proportion of clients work informally and their income is unstable (Cermeño et al., 2011). In this sense, to mitigate default risk, MFIs must develop analysis and evaluation tools adapted to their reality, which allow them to strengthen risk management (Abissi, 2019; Echeverri, 2006; Minzer, 2011; Rodríguez, 2019).

There is empirical evidence relating payment culture to a portfolio´s level of defaults and quality, in addition to autoregressive components including up to three lags, i.e., default indicators depend on past periods (Aguilar & Camargo, 2002; Cermeño et al., 2011; Coral, 2010; Saurina-Salas, 1998; Tuesta, 2018). Previous studies have also used explanatory variables such as the dynamism of national economic activity, the level of employability and income generation capacity (Ahumada & Budnevich, 2002).

Other variables that could explain the default risk are active interest rate, inflation, the type of activity financed, credit and technologies policies, incentives to the personnel in charge of promoting and recovering loans (Aguilar & Camargo, 2002; Cermeño et al., 2011). In this sense, high interest rates and level of liquidity could generate a greater financial burden, leading to the inability to repay in long-term (Cermeño et al., 2011; Rivera, 2020). Sociodemographic variables such as the number of family members, marital status, borrower gender, loan amount and number of installments to be paid have also been analyzed (González, 2010; Monsalve, 2009; Vargas and Mostajo, 2014; Zamudio, 2007).

Regarding client gender, it is argued that men are more likely to default on a microloan, while a portfolio with a higher share of women may have a lower default risk (Shahriar et al., 2020). On the other hand, a client with a large household is more prone to default, as he or she prioritizes family welfare in terms of health and food before the payment of financial obligations (Bekerman and Ozomek, 2003; Vargas and Mostajo, 2014).

In view of the prevailing conditions in the MFI market, this study analyzes the macroeconomic and microeconomic factors that affect default risk in a Costa Rican microfinance institution that provides financial solutions for individuals and small business to promote the local development in different regions of the country, the foregoing is carried out through associated community companies (EC) and through credit promoters. For this case, in 2019 the IMF had 4 938 clients, a female participation of 37%, 100% of loans were placed in rural areas, the average loan amount was US$2 368 and the PeR>30 was 5.6% (Redcamif, 2019).

This research aims to contribute with a basis for the design of econometric evaluation tools to identify the variables that impact default risk and that can be adapted to different Costa Rican and Central American MFIs, according to the characteristics of their client portfolios.

Based on this review, the paper is structured in five other sections: a) a theoretical reference to support the methodology used, b) methodological aspects used in the research, c) the main results obtained from the econometric analysis for MFI under study, d) a discussion section where the results obtained are contrasted with other research, and e) a section of conclusions on the main findings.

Theoretical referent

Panel data are an alternative to study different units over time, such as countries, financial entities, and economic sectors. Panel data can be solved with multiple linear regression analysis (Equation 1) and the Ordinary Least Squares (OLS) method (Gujarati & Porter, 2010):

$$Y_t = \beta_0 + \beta_1 X_{1t} + \cdots + \beta_k X_{kt} + \hat{u}_t \tag{1}$$

where:

Y_t : Dependent variable at period t;

X_{it} : Independent variables (up to the k-th variable) with their respective regression coefficients β, and

$\hat{u}_t$: Residual term.

Use of dummy variables in panel data allows modeling fixed effects to reflect the influence of unobservable factors and incorporate the effect that would be caused by omitted variables; the opposite case to random effects, which capture such effects in the residual term (Baronio & Vianco, 2014; Cermeño et al., 2011). The following is an econometric function for panel data with fixed effects (Equation 2) (Verbeek, 2017):

$$Y_{it} = \sum_{j=1}^{m} \alpha_j D_{ij} + X'_{it}\beta + u_{it} \tag{2}$$

where:

Y_{it} : Dependent variable of the unit i at period t;

X_{it} : Vector of independent variables with their respective regression coefficient (β), and

α_j : Fixed constants (dummy) capturing unobservable effects, where $D_{ij} = 1$ if $i = j$ and 0 otherwise.

The common intercept (β_0) is omitted to avoid perfect multicollinearity[2], which occurs when each individual (i) has a specific intercept (α_i), but there is also a common intercept (β_0) for all individuals; it is also assumed that X_{it} are independent to residual term (Gujarati & Porter, 2010).

The choice between the fixed effects method (FEM) and random effects method (MEA) depends on the convenience selection of samples, the research context, the number of observations and the conditional inference of the researcher (Baronio & Vianco, 2014; Mayorga & Muñoz, 2000). It is also recommended to use FEM when the cross-sectional units are smaller than the time periods (Cotler & Rodríguez-Oreggia, 2008).

Despite the importance of microcredit for improving the life quality and financial inclusion, it is evident the MFIs have little institutional, technological, and regulatory development to overcome to compete in local financial market (Rodríguez & Ruz, 2009; Steinhaeuser, 2013; Villalobos et al., 2003). In this regard, the public research available in Costa Rica has focused on studying the operating environment of MFIs (Gómez, 2012, p. 20; Hernández et al., 2015; L. Rodríguez & Ruz, 2009), but does not have the scope covered in this paper to study default risk.

In Latin America there are several studies available on default risk in MIFs, which were used as a reference for this study. One of these studies was published by Aguilar & Camargo (2002) in Peru, who used macroeconomic variables such as Gross Domestic Product (GDP) and inflation, and other credit variables such as the activity financed and staff incentive systems.

An inverse relationship has been identified between the economic cycle and default rates, i.e., in times of economic growth, default rates tend to decrease (Aguilar & Camargo, 2002; Ahumada & Budnevich, 2002; Zamore, et al., 2019; Rivera, 2020). This is because, in the macroeconomic aggregate, multiple effects are explained and related to each other. For Cermeño, et al. (2011) and Rivera (2020), the interest rate explains default since high interest rates can generate pressure on the payment of financial obligations.

From a general long-term view, periods of economic growth are congruent with periods of low and stable interest rates. This encourages private investment, productive activity, and better labor conditions, which translate into the availability of income to meet financial obligations (Ali & Daly, 2010; Bellotti & Crook, 2009; Coral, 2010; Clavi-

[2] Perfect multicollinearity in fixed-effects panel data does not require a statistical test to contrast it, since it is a theoretical problem.

jo-Ramírez, 2016; Cermeño et al., 2011; Coral, 2010; Lara et al., 2011; Loyaga, 2016; Rivera, 2020).

Other studies have also implemented microeconomic variables like gender, marital status, family size, reason for loan, amount and number of installments (González, 2010; Monsalve, 2009). Research by Chakravarty, et al., (2013) and Shahriar, et al., (2020) suggests that the average repayment rate of women is significantly better than male clients, due to decision making and planning. This analysis can be performed by separating the loan portfolio between female and male clients, or by using dummy variables that measure the effect of each type of client, as is done in this research.

Marital status suggests that a single person is more likely to default due to a commitment effect, as is a borrower with a large family who prioritizes family welfare over financial expenditure (Bekerman & Ozomek, 2003; Vargas y Mostajo, 2014).

Despite the logical explanation provided by the authors cited above, the effect of these variables may be ambiguous depending on the economic stability of the market niche, since a market niche with similar characteristics in the microeconomic variables, but with greater purchasing power, is less risky than a niche with less favorable economic indicators (Aguilar & Camargo, 2002).

The ambiguity of the effect on default may also be present in the amount and number of payments. Also, productive loans are less risky than commercial loans, and each productive activity has a different level of risk (Clavijo-Ramírez, 2016; Echeverri, 2006; Peg, 2016; Lara, et al., 2011; Schreiner, 1999; Steenackers & Goovaerts, 1989).

In addition to payment capacity and purchasing power, another important factor affecting the default risk is the payment culture (Tuesta, 2018). This is a complex variable to measure, as it depends on the macro and microeconomic factors mentioned above, among other social and cultural factors. It is common to incorporate the lagged component of default, on the understanding that a positive coefficient of the default lag signifies its gradual growth (Aguilar & Camargo, 2002; Andrade et al., 2019; Cermeño et al., 2011; Coral, 2010; Loyaga, 2016).

Methodology

Data and sample selection

Fifteen loan portfolios managed by the MFI´s partner Credit Enterprises (ECs) were studied. The size of the portfolios was US$6 million and represented about 53 % of the MFI's total portfolio as of February 2020.

The analysis period comprised the months of March-2017 and February-2020 (data cutoff), for a total of 36 monthly periods in which loans assigned to individuals with credit histories greater than 75 % of the amount of quotas assigned were considered. The sample size was 6 432 credits and was carried out by convenience based on the availability of the required information; it was neither probabilistic nor random.

Due to the complexity of data management and the variability of microloans managed by different Credit Enterprise, the monthly information was grouped and averaged according to the activities financed (Appendix 1)[3]. In this way, 15 econometric models were obtained that forecast the average of default days (MR) in each loan portfolio, with respect to the average characteristics of the clients and microloans. The grouping of data made it possible to obtain a balance in the time observations. Table 1 summarizes the independent variables used in this research and by other authors.

Econometric analysis of non-performing loans

A statistical description was made of the variables used, with measures such as the mean, standard deviation, and coefficient of variation in quantitative variables. Frequency distributions were also used for qualitative variables. Subsequently, fifteen econometric models are proposed to analyze the relationship between independent variables (Table 1) and the average days of default (MR, as the dependent variable) for each loan portfolio, using multiple linear regression analysis and the OLS method in balanced panel data. It should be noted that, due to the characteristics of the variables, in some cases logarithmic transformation can be applied to reduce the volatility of the time series.

[3] As far as possible, grouping was carried out among activities that had some relationship, if there is a balance in the temporal observations.

Table 1. Description of the variables used in econometric modeling.

Variable	Code	Description	Source
Default lag	MR_{t-n}	Average days of default recorded in the previous period.	Aguilar & Camargo (2002), Cermeño et al. (2011), Coral (2010), Loyaga (2016), Saurina-Salas (1998), Schreiner (1999), Toast (2018).
Financed activity	GA	Cross-sectional unit dummy variables representing groups of financed activities with intrinsic characteristics.	Aguilar & Camargo (2002), Lara et al. (2011), Schreiner (1999), Steenackers & Goovaerts (1989).
Loan amount	MT	Higher loan amounts could generate future inability to pay.	Clavijo-Ramírez (2016), Echeverri (2006), Lara et al. (2011), Schreiner (1999).
Installments	CT	Higher installments lead to more uncertain future scenarios regarding loan recovery.	Echeverri (2006), Lara et al. (2011), Salazar (2013), Steenackers & Goovaerts (1989)
Interest rate	IT	Reflects the increase in the cost of loans as a negative effect on repayment capacity.	Aguilar & Camargo (2002), Bellotti & Crook (2009), Clavijo-Ramírez (2016), Cermeño et al. (2011),Coral (2010), Lara et al. (2011), Loyaga (2016), Rivera (2020).
Gender	GN	Dummy variable, where female = 0 and male = 1. Males are more likely to default than female.	Clavijo-Ramírez (2016), Echeverri (2006), Lara et al. (2011), Salazar (2013), Schreiner (1999), Shahriar et al. (2020), Steenackers & Goovaerts (1989).
Civil estatus	CE	Categorical variable, where single = 1, common-law = 2, married = 3, divorced = 4 and widowed = 5. Clients in a formalized marital status are more likely to repay.	Clavijo-Ramírez (2016),Echeverri (2006), Lara et al. (2011), Steenackers & Goovaerts (1989), Vargas & Mostajo (2014).
Number of children	HJ	Proxy variable measuring family size. A client with more children is more likely to default.	Bekerman & Ozomek (2003), Steenackers & Goovaerts (1989).
Economic dynamism[1]	IMAE	Monthly Index of Economic Activity. Increases in the index reflect improvements in production, in the population's income and in its ability to pay.	Aguilar & Camargo (2002), Ahumada & Budnevich (2002), Ali & Daly (2010), Bellotti & Crook (2009), Coral (2010), Lara et al. (2011), Loyaga (2016).
Unemployment rate[1]	DE	Increases in the unemployment rate decrease the income of the population and its ability to pay.	Ahumada & Budnevich (2002), Bellotti & Crook (2009), Coral (2010), Lara et al. (2011), Loyaga (2016).

Study units (cross-sectional units) were constituted with the activities financed (Appendix 1) and each has the same number of observations. Fixed effects are assumed to measure the influence of financed activities on delinquency in loan portfolios and to capture unobservable effects.

In general terms, the econometric model used to analyze the default is algebraically represented as follows:

$$Y_{it} = \alpha_1 D_{1i} + \cdots + \alpha_1 D_{mi} + \beta_1 X_{1it} + \cdots + \beta_k X_{kit} + u_{it} \tag{3.1}$$

$$MR_{it} = \alpha_1 D_{1i} + \cdots + \alpha_m D_{mi} + \beta_1 MT_{it} + \beta_2 CT_{it} + \beta_3 TS_{it} + \beta_4 SX_{it} + \beta_5 EC_{it} + \beta_6 HJ_{it} + \beta_7 IMAE_{it} + \beta_8 DE_{it} + u_{it} \tag{3.2}$$

D_i **: are dummy variables that capture the fixed effects of the groups of activities financed.**

To choose the models with the best fit, the following parameters were used: the coefficient of determination R2, measures the goodness of fit (the higher the better the model); the adjusted R2, penalizes the use of independent variables; the Akaike (AIC) and Schwarz (SIC)[4] information criteria, as a prediction bias parameter (the lower the criteria, the greater the predictive capacity of the model).

White's heteroskedasticity test and Wooldridge's autocorrelation test were used. To correct for heteroskedasticity, the Weighted Least Squares (WLS) method was applied, which assigns a higher weight to the observations with less variability, and vice versa (Cameron & Trivedi, 2005; Greene, 2003). With this method, the original variables are transformed with a weight w that considers the heteroskedastic variance (σ_t^2), as follows:

$$\frac{Y_{it}}{w} = \alpha_1 \frac{D_{1i}}{w} + \cdots + \alpha_1 \frac{D_{mi}}{w} + \beta_1 \frac{X_{1it}}{w} + \cdots + \beta_k \frac{X_{kit}}{w} + u_{it} \tag{4}$$

In cases with autocorrelation, the Feasible Generalized Least Squares (FGLS) method was applied with the Cochrane-Orcutt (CO) procedure. This method consists of subtracting the original regressions and in first differences multiplied by σ (Equation 5.1 and 5.2) (Gujarati & Porter, 2010). The new correlation coefficients are retransformed for the qualitative as shown below (Equation 6):

$$Y_{it} - \rho Y_{it-1} = \alpha_1(D_{1it} - \rho D_{1it-1}) + \cdots + \alpha_m(D_{mit} - \rho D_{mit-1}) + \beta_1(X_{1it} - \rho X_{1it-1}) + \cdots + \beta_k(X_{kit} - \rho X_{kit-1}); \tag{5.1}$$

$$Y_{it} - \rho Y_{it-1} = \gamma_1(D_{1it} - D_{1it-1}) + \cdots + \gamma_m(D_{mit} - D_{mit-1}) + \beta_1^*(X_{1it} - X_{1it-1}) + \cdots + \beta_k^*(X_{kit} - X_{kit-1}); \tag{5.2}$$

$$\therefore \gamma_1 = \alpha_1(1-\rho) \Rightarrow \alpha_1 = \frac{\gamma_1}{(1-\rho)} \tag{6.1}$$

$$\therefore \beta_k^* = \beta_k(1-\rho) \tag{6.2}$$

To choose the models with the best fit, the following parameters were used: the coefficient of determination R2, measures the goodness of fit (the higher the better the model); the adjusted R2, penalizes the use of independent variables; the Akaike (AIC) and Schwarz (SIC)[5] information criteria, as a prediction bias parameter (the lower the criteria, the greater the predictive capacity of the model).

[4] Known as Bayesian Information Criterion (BIC).

[5] Known as Bayesian Information Criterion (BIC).

Resultados

The loans included in this analysis were placed with an average amount of US$1 740, a 36-month term and an interest rate of 26 %. Most of the loans were assigned to male clients who were married and without children. Fifty-one percent of the loans were never default (category S) and the remainder fell into the following categories[6]: 20 % in A, 9 % in B, 4 % in C, 6 % in D and 10 % in E. Figure 1 shows the characteristics of the portfolios according to the maximum default recorded.

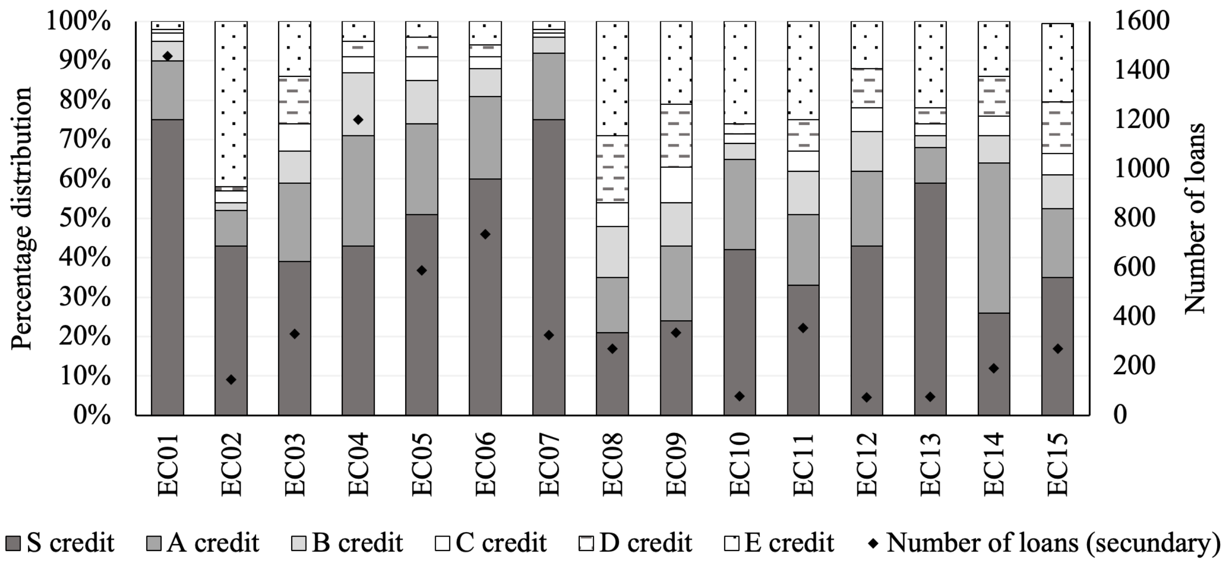

Figure 1. Number of loans by credit enterprise (EC)1 and percentage according to maximum past due, 2017-2020.

1/ The order of the portfolios appears based on the percentage participation in the total loan portfolio.

In loan portfolios EC08 and EC09, less than 50% of the loans had a maximum default of less than 31 days, while portfolio EC02 had the highest percentage of category "E loans". Notably, the EC01 portfolio had the largest number of loans, the largest share of MFI's total portfolio (14 %) and the lowest number of loans with historical records of default and is therefore taken as a model portfolio for the MFI.

In the first stage of econometric modeling, all variables described in Table 1 were used. However, no model had the desired indicators in terms of its ability to forecast default. This could have been due to heteroskedasticity and autocorrelation that lead to

[6] Categories according to default days: A from 0 to 30, B from 31 to 60, C from 61 to 90, D from 91 to 180 and E more than 180.

non-significant and biased coefficients that undefine the econometric function, or coefficients signs contrary to economic theory (Table 1).

To obtain models with best forecast fit (Appendix 2), different combinations between independent and dependent variable were applied, with different logarithmic functional forms and correction for heteroskedasticity and autocorrelation with WLS and FGLS methods.

All models presented improvements in the decision parameters and significant regression coefficients, except for the intercepts of some cross-sectional units (e.g., portfolios EC06, EC07, EC13 and EC15). In these specific cases, the non-significance suggests that the set of financed activities dostock purchasees not affect the level of portfolio default. For example, Appendix 2 shows in EC06 portfolio, the "GA2" activity is not significant (p-value = 0.22), so that jointly financing commerce, stock purchase and manufacturing (Table 1), does not generate a significant change in portfolio´s default indicators.

An opposite case occurs in the same EA06 portfolio for GA1 activity set of agricultural, forestry and fishing (Appendix 1), since its coefficient is significant at 95% confidence level (p-value = 0.02%) (Appendix 2). These results suggest higher default levels in GA1 activities, so that business strategies should be implemented to control the default probability and recover the loan portfolio.

Another case is the EC08 portfolio due to the lack of activity diversification in the sample used, since it only finances agriculture, forestry, fishing and commerce (GA1) and personal loans (GA2). In this case, Appendix 2 shows that both groups of activities affect delinquency significantly (GA1 p-valor = 0.02; GA2 p-valor = 0.05). However, the magnitude of the regression coefficient (GA1 = 1.44; GA2 = 1.75) shows delinquency levels are more sensitive to personal loans (GA2) because most of them are non-performing loans that do not directly generate cash flow and are considered as expenses.

On the other hand, the procedures applied to correct for heteroskedasticity and autocorrelation were efficient according to White and Wooldridge tests (Appendix 2). In addition, the common independent variable in all loan portfolios is the default lag, one or two periods (MR_1 y MR_2), as in the case for portfolios EC01 and EC15.

This suggests that delinquent clients may maintain their default status in several consecutive periods. The variables MT, CT, CE and IMAE were not significant, so they are not included as regressor in any model. While the activities financed (GA) could influence the borrowers' repayment capacity for some portfolios, mainly because of the characteristics of the financed activities and their capacity to generate cash flow to meet the financial obligations.

To interpret the regression coefficients, the EC01 portfolio is taken as an example. In this case it is shown that financing the GA3[7] group of activities is less risky than the other activities, because the regression coefficient (10.94, which intrinsically represents the average days of default for financing this type of activity) is comparatively lower than the other groups of activities (GA1, GA2 and GA4). On the other hand, the default level is sensitive to the interest rate (IT): for every 1% increase in IT, the average default increases by 0.076 days. As for lagged defaults in periods t-1 and t-2, the defaulting debtor increase average default by 0.53 and 0.29 days respectively, as an effect of the payment culture and its own characteristics.

In loan portfolios EC03, EC04, EC09, EC11 and EC12, the variables DE, HJ and GN were significant. The results suggest that client risk increases when unemployment (DE), number of children (HJ) and financing male clients (GN) are more recurrent. For the EC12 loan portfolio, financing a male client (GN) increases average portfolio delinquency by 0.19 days. For the EC11 portfolio, when the number of children increases by 1 %, the average delinquency could increase to 2.23 % days (this interpretation applies by logarithmic transformation).

Discussion

The arguments addressed in the literature review confirm the results of this research regarding the use of lags to explain the default risk. In this sense, high default levels are detrimental to future portfolio quality due to its autoregressive component as a quantitative proxy variable of payment culture (Aguilar & Camargo, 2002).

Research in Peru demonstrates the autoregressive effect on the quality of a loan portfolio. In this sense, a positive regression coefficient in lagged component of delinquency expresses the loss of quality over time and may be the cause of poor indicators of portfolio quality if operational actions were not adequately managed to recover the savings placed in the market (Cermeño et al., 2011). This finding is like the results of this research, e.g., in portfolios EC02 and EC03 the impact of lagged defaults is 98 % and 94 %, which makes them highly susceptible to quality loss quality and puts at risk the loan recovery, impacting in the long term their participation in new market niches to diversify business risk.

One explanation of the effect of lagged defaults is provided by Saurina-Salas (1998), who points out that default's loans did not change its status immediately in the companies' balance sheets and could be remain for up to three years in the respective management process. This situation is seen in the 15 portfolios studied, since its defaulted loans do not affect immediately affect the MFI´s cash flows, since the MFI´s is protected by the interest rate differential and equity contributions.

[7] Consisting of construction activities (Appendix 1).

Regarding the economic sector of the activities financed, Clavijo-Ramírez (2016) identified higher default rates in clients with activities in the mining, commerce, and industry sectors in Colombia, due to instability in income flow. These differences could explain why some financed activities are more significant than others in their effect on default in loan portfolios. For EC06 portfolio, financing agricultural and non-productive activities (GA4: education, personnel, and health) affects the default level, contrary to construction activities (GA3) and commerce, stock purchase, manufacturing, and services (GA2).

The explanation for this differential effect depends on the industry´s macroeconomic conditions, mainly due to the stability of production growth cycle and the capacity to generate cash flow. Regarding agricultural activities, the borrower´s operational capacity should also be considered to reduce risks that cannot be fully mitigated, such as climatic phenomena that affect harvest, or the production cycle characterizing the activity, since seasonal fruit crops generate a different cash flow than short-cycle vegetable crops.

A similar effect occurs between productive and consumer loans. According to Coral (2010), it is normal for consumer loans to present higher levels of default since it is assumed as an expense and its payment depends on productive activities and risks such as unemployment or business management. In addition, consumer loans may affect the borrower's ability to pay if they are not acquired in a premeditated way, which represents a risk to the lending institution.

The interest rate (IT) was found to be significant, since higher loan costs put pressure on the financial burden of risky borrowers (Rivera, 2020), as did unemployment, gender, and the number of children. Coral (2010) found that if employment decreases at the macroeconomic level, the overall income level of the population is negatively affected and leads to a lower payment capacity.

In a microfinance institution in Argentina, 31 % of uncollectible accounts fell on families with more than four children, and the economic burden in daily expenses was detrimental to meeting financial obligations (Bekerman & Ozomek, 2003). Finally, it is common for financing to women to be less risky (Schreiner, 1999), as shown by the results for the EC12 portfolio. In a Colombian case study, Salazar (2013) found statistical significance in the variable categorizing the gender of borrowers, as did Bellante & Green (2004). These findings suggest that women are more risk-averse and their propensity to make risky decisions is lower.

Conclusions

The MFI under study has not historically faced delinquency levels that exceed control margins. This made the econometric modeling difficult, and it was necessary to use different combinations of independent and dependent variables, with logarithmic functional forms in some cases.

On the other hand, the main limitation for this research was the high degree of heterogeneity in the data made it impossible to perform a standardized analysis for all the loan portfolios, so the balanced panel data FEM method was used, which facilitated the incorporation of independent variables such as the activities financed. Also, the WLS and FGLS procedures were effective in correcting for heteroskedasticity and autocorrelation.

The results show that, depending on the loan portfolio and client characteristics, delinquency is affected by autoregressive components, the activities financed, unemployment and the interest rate, as well as by sociodemographic variables such as gender and number of children. Therefore, it is recommended to use these variables in future research and the design of methodological tools to strengthen default risk management in microfinance institutions.

Despite the results obtained, alternative studies with annual time series could facilitate the analysis of sensitive indicators such as the default risk for microfinance institutions, since it would be possible to visualize more precisely the trends of economic cycles and the effect of macroeconomic variables on delinquency in loan portfolios.

This methodological proposal foresees the strengthening of the analysis process in the credit granting and the definition of less risky market niches for the MFI under study. Although, we encourage the use of our findings as a basis for the field of MFI research because of the positive impact they have on the fight against poverty and the promotion of financial inclusion. We also urge the adaptation of enabling tools for the MFI industry in national legislation to facilitate and improve their conditions of competition against traditional financial banking, to improve access to credit for small enterprises.

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Appendix

Appendix 1. Grouping of activities financed by loan portfolio (EC)[1]

Category	EC01	EC02	EC03	EC04	EC05	EC06	EC07	EC08	EC09	EC10	EC11	EC12	EC13	EC14	EC15
Agriculture, forestry and fishing	GA1	GA1	GA1	GA1	GA1	GA1	GA1	GA1	GA1	GA1	GA1	GA1	GA1	GA1	GA1
Commerce	GA2	GA2	GA1	GA1	GA1	GA2	GA1	GA1	GA1	GA1	GA1	GA1	GA2	GA1	GA1
Stock purchase[2]	GA2		GA1			GA2	GA1				GA1				
Construction	GA3	GA1	GA1	GA1	GA2	GA3	GA1		GA1	GA1	GA1	GA1	GA1	GA1	GA1
Education	GA4	GA3	GA2	GA2	GA3	GA4	GA2		GA2	GA2	GA2			GA2	
Manufacturing industry	GA2	GA1	GA1		GA1	GA2	GA1		GA1	GA1	GA1	GA1		GA1	GA1
Personal[3]	GA4	GA3	GA2	GA2	GA3	GA4	GA2	GA2	GA2	GA2	GA2	GA2	GA2	GA2	GA2
Health	GA4	GA3			GA3	GA4	GA2		GA2		GA2			GA2	
Services	GA2			GA1	GA1	GA2	GA1		GA1	GA1	GA1	GA1	GA2	GA1	GA1
Transport and storage	GA2	GA1			GA1		GA1		GA1	GA1	GA1	GA1		GA1	

1/ The grouping of activities differs in most companies. For example: in the EC01 portfolio, the GA1 grouping consists of primary production activities (agriculture, livestock, forestry, and fishing) and in the EC04 portfolio it also includes commercial, construction and service activities.

2/ It finances the affiliation of clients to the Credit Enterprise (EC).

3/ Classifies loans acquired to finance maintenance and purchase of equipment and machinery that could not be related to any productive activity due to lack of information.

Appendix 2. Models with best fit and correction for heteroskedasticity and autocorrelation by loan portfolio.

Portfolio	Dependent variable[1]	Independent variable	Coef.	Coef. Tran[2]	p-Value	R^2	R^2 adj	AIC	SIC	White test[3]	Wooldridge test[3]
EC01	MR_WLS	GA1_WLS	12.15		0.01 ***	0.96	0.80	587.89	607.86	27.71 (0.53)	-0.25 (0.82)
		GA2_WLS	13.33		3.2E-03 ***						
		GA3_WLS	10.94		0.01 ***						
		GA4_WLS	14.01		2.2E-03 ***						
		l_IT_WLS	7.65		0.01 **						
		MR_WLS_1	0.53		6.1E-09 ***						
		MR_WLS_2	0.29		5.0E-04 ***						
EC02	l_MR	GA1	3.12		3.0E-03 ***	0.95	0.94	-57.00	-43.73	11.10 (0.44)	-0.70 (0.56)
		GA2	3.08		3.1E-03 ***						
		GA3	3.16		3.2E-03 ***						
		l_IT	2.33		0.01 ***						
		l_MR_1	0.98		5.6E-51 ***						
EC03	l_MR	GA1	0.73		0.05 *	0.98	0.98	-150.21	-141.22	8.70 (0.37)	2.32 (0.26)
		GA2	0.69		0.06 *						
		l_DE	0.20		0.10 *						
		l_MR_1	0.94		5.2E-40 ***						
EC04	l_MR_WLS	GA1_WLS	3.84		7.0E-04 ***	0.99	0.97	370.44	379.32	12.72 (0.47)	1.85 (0.32)
		GA2_WLS	4.25		8.0E-04 ***						
		l_DE_WLS	1.25		1.5E-03 ***						
		l_MR_WLS_1	0.62		2.5E-06 ***						
EC05	l_MR_CO	GA1_CO	11.90	10.11	0.08 *	0.89	0.89	39.74	52.87	10.35 (0.50)	0.61 (0.60)
		GA2_CO	11.90	10.11	0.08 *						
		GA3_CO	12.09	10.27	0.07 *						
		l_IT_CO	8.74		0.09 *						
		l_MR_CO_1	0.76		1.2E-29 ***						
EC06	MR_WLSCO	GA1_WLSCO	0.93	0.69	0.02 **	0.99	0.98	521.67	536.08	19.20 (0.16)	0.10 (0.93)
		GA2_WLSCO	0.52	0.38	0.22						
		GA3_WLSCO	0.13	0.10	0.53						
		GA4_WLSCO	4.92	3.64	6.0E-04 ***						
		MR_WLSCO_1	0.94		1.5E-79 ***						
EC07	MR_WLSCO	GA1_WLSCO	0.17	0.13	0.17	0.94	0.84	290.72	297.29	12.13 (0.15)	-2.41 (0.25)
		GA2_WLSCO	0.89	0.72	2.3E-03 ***						
		MR_WLSCO_1	0.88		3.8E-29 ***						
EC08	MR_WLS	GA1_WLS	1.44		0.02 **	0.99	0.98	317.16	323.82	7.19 (0.52)	-0.05 (0.97)
		GA2_WLS	1.75		0.05 **						
		MR_WLS_1	1.01		3.7E-64 ***						
EC09	l_MR	GA1	3.22		0.01 ***	0.89	0.88	7.78	16.78	7.43 (0.49)	-2.37 (0.25)
		GA2	3.15		0.01 ***						
		l_DE	1.01		0.01 ***						
		l_MR_1	0.79		4.3E-15 ***						
EC10	l_MR_CO	GA1_CO	1.09	2.32	3.0E-02 ***	0.84	0.83	-15.69	-9.04	5.52 (0.24)	0.40 (0.76)
		GA2_CO	1.33	2.82	0.01 ***						
		l_MR_CO_1	0.79		5.3E-15 ***						
EC11	l_MR	GA1	3.33		2.5E-05 ***	0.72	0.71	7.18	18.43	10.97 (0.61)	0.22 (0.86)
		GA2	3.23		2.4E-05 ***						
		l_HJ	2.23		3.0E-04 ***						
		l_DE	0.96		8.0E-04 ***						
		l_MR_1	0.48		7.2E-06 ***						

1/ "l_" represents logarithmic transformation, "WLS" represents heteroskedasticity correction, and "CO" represents autocorrelation correction (methodology section).

2/ Cochrane-Orcutt (CO) require an algebraic transformation in regression coefficients of qualitative variables.

3/ Contrast statistic and the p-value (* represents significance at 10%; **, at 5%; ***, at 1%).

Appendix 2. Models with best fit and correction for heteroskedasticity and autocorrelation by loan portfolio.

Portfolio	Dependent variable[1]	Independent variable[1]	Coef.	Coef. Tran[2]	p-Value	R^2	R^2 adj	AIC	SIC	White test[3]	Wooldridge test[3]
EC12	l_MR	GA1	0.63		0.01 ***	0.83	0.82	20.90	29.90	4.87 (0.56)	0.17 (0.89)
		GA2	0.68		0.02 **						
		GN	0.19		0.06 *						
		l_MR_1	0.80		4.0E-17 ***						
EC13	MR	GA1	44.04		0.12	0.70	0.69	845.47	852.21	7.36 (0.12)	0.82 (0.56)
		GA2	76.94		0.04 **						
		MR_1	0.85		2.5E-16 ***						
EC14	MR	GA1	6.58		0.03 **	0.74	0.73	551.29	558.04	4.02 (0.40)	-1.34 (0.41)
		GA2	13.43		2,8E-03 ***						
		MR_1	0.77		7.9E-16 ***						
EC15	MR_WLS	GA1_WLS	3.85		0.05 *	0.97	0.67	335.95	344.71	17.70 (0.17)	-0.76 (0.59)
		GA2_WLS	3.40		0.35						
		MR_WLS_1	0.58		9.2E-06 ***						
		MR_WLS_2	0.40		3.8E-03 ***						

1/ "l_" represents logarithmic transformation, "WLS" represents heteroskedasticity correction, and "CO" represents autocorrelation correction (methodology section).

2/ Cochrane-Orcutt (CO) require an algebraic transformation in regression coefficients of qualitative variables.

3/ Contrast statistic and the p-value (* represents significance at 10%; **, at 5%; ***, at 1%).