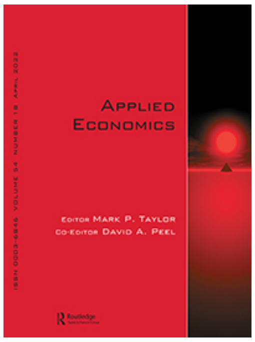

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The effects of pricing strategy on the efficiency and self-sustainability of microfinance institutions: a case study

María Patricia Durango[a], Juan Lara-Rubio[b], Andrés Navarro Galera[b] and Antonio Blanco-Oliver[c]

[a]EAFIT University, Medellin, Colombia; [b]University of Granada, Granada, Spain; [c]University of Seville, Seville, Spain

ABSTRACT

To become financially self-sustainable, Microfinance Institutions (MFIs) trigger a schism in their management modes, thereby promoting efficiency and competitiveness. The increase of competition in the microfinance sector motivated by the entry of banks into this industry is another incentive for MFIs to implement advanced management systems. Pricing systems and credit-scoring models should contribute towards the efficiency of MFIs, thereby improving their competitiveness and self-sustainability in an increasingly constrained environment. However, to the best of our knowledge, no empirical evidence exists on the application of pricing strategies by MFIs. Therefore, this paper builds a microcredit-pricing system and determines the capital requirements inspired by the Basel III Internal-Rating Based (IRB) approach, which is underpinned by multilayer perceptron (MLP) credit-scoring. We find that the implementation of an IRB approach allows the analysed MFI to reduce its capital requirement and current interest rates by $200,000 and 30.12%, respectively. Moreover, this approach constitutes a relevant tool for the control of credit risk and the minimization of default losses. Consequently, the adoption of pricing and credit-scoring systems provides MFIs with a power management tool to compete against banks by reducing the interest rate, capital requirements, and credit losses, and therefore increases their financial self-sustainability.

KEYWORDS

Microfinance institution; efficiency; self-sustainability; internal rating-based approach; pricing; multilayer perceptrom

JEL CLASSIFICATION

G21; L11; O31; C45

I. Introduction

The current trend in the microfinance industry is a shift away from donor-funded institutions towards commercially sustainable operations (Bassem 2009; Montgomery and Weiss 2011). In Latin America, bilateral and multilateral aid and aid from private providers and other resource flows have decreased by 16% between 2018 and 2019 (OECD 2021). Although this transformation has been taking place since the end of the last century (Morduch 1999), it has been only in recent years that it has acquired key strategic relevance because the survival of MFIs is now at risk. The principal factors that have highlighted the importance of sustainability of MFIs and that threaten their continuity include on the one hand, the current negative economic situation, for Africa and America it represented an 81% drop in the informal economy due to the crisis (IADB 2020), which is causing a decrease in both donations received and microcredits conceded by MFIs[1] (Wagner and Winkler 2013), despite of the fact that investment in microfinance provide adequate risk-adjusted performance (Janda and Svárovská 2010). And, on the other hand, the increased competition in the microfinance sector (Assefa, Hermes, and Meesters 2012), especially that exerted on the part of the commercial banks which have emerged in microfinance (downscaling[2]). Thus, even though in 2015 these commercial banks accounted for just 20% of the total microfinance institutions, they represented 95% of the total microcredit portfolio in Latin America and the Caribbean (Trujillo and Navajas 2016).

Nevertheless, and in contrast to the general belief argued by some micro-lenders which suggests that to achieve financial sustainability, it is to necessary increase the microcredit interest rates, the empirical evidence suggests that the way to reach sustainability, MFIs require a lower level of leverage and collect savings (Hartarska and

CONTACT María Patricia Durango mdurango@eafit.edu.co EAFIT University, Medellin, Colombia

[1]According to Wagner and Winkler (2013), in the crisis years, microcredit growth dropped by about 13%, with the average real credit growth rate at 25% p.a.

[2]Downscaling can be defined as a process by which a bank, or another formal financial institution, expands its services to work with clients traditionally served by MFIs.

Nadolnyak 2007). Along these lines Roberts (2013) and Cuéllar-Fernández et al. (2016) demonstrates that a stronger for-profit orientation corresponds with higher interest rates for MFI clients, but that this does not contribute towards greater profitability and therefore sustainability because the greater orientation to profits is also associated with operating cost, being one of the most relevant factor of MFI. Therefore, the new focus on self-sustainability triggers a schism in the management of microfinance institutions, mainly promoting: (a) efficiency in all their processes, (b) the reduction of the microcredit default loss rate (which increments on increasing competition in the microfinance sector (Guha and Chowdhury 2013), (c) the assignment of risk-adjusted interest rates for each applicant (pricing model).

These three management improvements can be achieved by means of use of pricing strategies. Nevertheless, to assign interest rates adjusted to the risk of each borrower (pricing model), it is necessary to evaluate the credit risk of each applicant, for which it is necessary to develop a credit-scoring model.

Credit-scoring systems offer several major advantages to the financial intermediaries who adopt them: the cost of credit analysis is reduced, cash flow is improved, faster credit decisions are enabled, losses are reduced, a closer monitoring of existing accounts is possible, and prioritizing collections are allowed (West 2000), and, therefore, these models can be considered as management tools that can help to increase efficiency and reduce microcredit default losses of MFIs (Bekhet and Kamel 2014). In this sense, credit scoring is one of the most important uses of technology that may affect management of MFIs, and according to Schreiner (2004) the experiments carried out in Bolivia and Colombia show that the implementation of credit scoring improves the judgement of credit risk and thus cuts the costs of MFIs by more than $75,000 per year.

Therefore, pricing and credit-scoring models are two complementary tools based on the Basel III Internal-Rating Based (IRB) approach (Basel III, 2017) that provide MFIs with relevant management improvements in terms of more efficiency and lower default losses (West 2000), more risk-sensitive capital requirements (Repullo and Suarez 2004) and interest rates better adjusted to the risk of each borrower (Ruthenberg and Landskroner 2008).

The main goal of this study is to provide a solution so that MFIs can determine the microcredit pricing and capital requirements based on a Basel III IRB approach, which uses a multilayer perceptron (MLP) credit-scoring to model the probability of default. Moreover, we benchmark the performance of the above model against two IRB models which determine the probability of default using logistic regression (LR), with respect to the Basel II standardized approach (BCBS, 2006). To attain the above objectives, a large sample from a Colombian MFI is used which contains financial, non-financial and macroeconomic variables of almost 3,000 borrowers.

II. Data and variables

The data set

We use a data set of microcredits from a Colombian Microfinance Institution. Colombia is a country with broad experience in MFI activity and these institutions have achieved a high rate of penetration in this country. In Colombia, they have a combined portfolio of 1.4 billion dollars and serve 1.4 million clients (Pedroza 2010). International organizations (IADB 2016; World Bank 2014) and researchers (Lin and Sung 2017) have reported that Colombia's MFIs promote small business activity and financial inclusion as a public policy priority, as a result of which this country provides one of the best environments in the world for the microfinance industry to flourish.

For Colombia, the information analysed was obtained from the database published by Encumbra (www.encumbra.com.co), which contains 2,627 observations for the period 2012–2015, with information on loans to clients in low-income populations, small businesses and those with little access to traditional banking intermediation. This period is suitable and timely because at the beginning of the economic recovery (estimated by international organizations in 2012), the number of microcredits took an upward path, caused by a greater participation in the market, the appearance of new specialized entities and the strengthening of existing ones, which went from being cooperatives and NGO to formally constituted microbanks. According to the statistics published by Colombian Financial Superintendency (Superintendencia Financiera de Colombia) 17,000 million dollars were lended in microcredits during the 2015.

This MFI offers three credit products (fixed assets, working capital and consumption) and grants loans ranging from small amounts up to 120 times the current legal monthly minimum wage, in accordance with the legal requirements established by the Colombian Financial Superintendency (*Superintendencia Financiera de Colombia)* (Reg. No. 2014056513-007 of 13 April 2015) and with a duration of 1–36 months.

The information is related to personal characteristics, financial ratios of their microenterprise, and other variables related to the macroeconomic context and any delays in the payment of a microcredit fee. To perform an appropriate comparison of the classification models (LR and MLP), our final data set is randomly split into two disjoint sub-sets; a training set of 75% and a test set of 25%. The configuration of parameters of each model is selected through a 10-fold cross-validation procedure (for more details see Hastie, Tibshirani, and Friedman 2009). One advantage of cross-validation is that the credit-scoring model is developed with a large proportion of the available data (75% in this case).

The Colombian MFI is appropriate for our research aims for the following reasons: a) It provides sufficient information on client payment behaviour, both qualitative and quantitative, with socio-demographic, financial and macroeconomic data, which is in line with the approach taken by Blanco et al. (2013), Van Gool et al. (2012) and Karlan and Zinman (2011); moreover, by focusing on a study period of four years we can examine the impact on MFI lending growth of specific variables (Shahriar and Garg 2017; Shahriar et al. 2016) and according to Quayes (2012) with accurate financial information from highly disclosed MFI to have better data reliability, b) we have data from randomly selected samples of loan portfolios, containing each of the explanatory variables included in the model; c) the observations taken from the Colombia database represent 36% of its total microcredit portfolio, and so it is acceptably representative.

Dependent variable

The dependent variable in the proposed statistical model is a dummy variable with a value of 1 for loans that are in arrears for at least one payment and have a cost for the lender, and a value of 0 for loans with no payment delay producing added cost for the lender. In line with other studies (Blanco et al. 2013; Rayo, Lara, and Camino 2010; Schreiner 2002), a microcredit presenting a delay in repayment of at least thirty days is defined as default microcredit. However, in this paper, we adopt the criteria set out in the Basel III regulations for the measurement of credit risk and of good practices in risk management. According to the BCBS (2017), an MFI loan should be considered in default after a payment delay of 90 days. Basel III provides a legal framework for financial globalization, requiring institutions to have sufficient assets to ensure their solvency and to protect the interests of depositors and creditors. However, further strengthening of this prudential supervision and regulation framework is needed to enable a timely, effective response to fresh challenges, particularly in view of potential decreases in financial flows to emerging markets and the resulting impact on domestic financial stability.

Following the recommendations of the Bank for International Settlements (BIS 2015), the aim of our study is to improve upon the standard approach to the management of credit risk, by reducing national discretion and the use of external credit ratings, replacing them with the analysis of relevant risk factors that are clearly identifiable, measurable and consistent across jurisdictions.

Description of input variables

Table 1 shows the input variables used in this study. These provide the various characteristics of borrowers, lenders, and loans. Numerous qualitative variables are considered in our study, since: (a) Schreiner (2004) suggests that the input variables of credit scoring forces the microfinance sector to be more qualitative and

Table 1. Independent variables.

VARIABLE	DESCRIPTOR	TYPE	CONCEPT	EXPECTED SIGN (β)
			IDIOSYNCRATIC VARIABLES	
			Non-financial variables	
Gender	GENDER	Dichotomous	0 = Male; 1 = Female	-
Marital status	MARITAL	Dichotomous	0 = Single; 1 = Married/Cohabiting	-
Age	AGE	Numerical	Age at the time of loan application	+
Business sector	SECTOR	Categorical	Area of economic activity: 0 = Trade; 1 = Industry; 2 = Services	-/+
Residence	ZONE	Dichotomous	0 = Urban; 1 = Rural	-
Employment situation	EMPT_SIT	Dichotomous	0 = Self-employed; 1 = Employed	-
Education	EDUCATION	Categorical	0 = High school; 1 = Technical qualification; 2 = University	-
Client history	HISTORY	Numerical	Number of continuous months as a MFI client	-
Creditworthiness	CR_WTH	Categorical	According to MFI, 0 = Normal; 1 = Some issues; 2 = Weak; 3 = Doubtful	+
Number of loans granted previously	LOAN_GRANT	Numerical	Number of loans granted previously by the MFI	-
Number of loan applications refused	LOAN_REF	Numerical	Number of loan applications refused previously by the MFI	+
Repayments unmet	UNPAID	Numerical	Number of payments in default	
Payment delay	DELAY	Numerical	Loan delay (days)	+
Average arrears	ARREARS	Numerical	Average arrears (days)	+
			Financial ratios	
Liquidity turnover	R1	Numerical	Repayment capacity/Income x 360	+
Productivity	R2	Numerical	Gross income/Operating costs	-
Liquidity	R3	Numerical	Repayment capacity/Total liquid assets (%)	-
Debt ratio	R4	Numerical	Liability /(Liability + Equity) (%)	+
Leverage	R5	Numerical	Liability/Equity (%)Liability/Equity (%)	+
ROA (Return on assets)	R6	Numerical	Net income/Assets (%)	-
ROE (Return on equity)	R7	Numerical	Net income/Equity (%)	-
			Loan variables	
Amount of loan	AMOUNT	Numerical	Amount of loan (USD)	+
Duration of loan	DURATION	Numerical	Number of monthly instalments	+
Purpose of loan	PURPOSE	Categorical	0 = Fixed assets; 1 = Working capital	-
Guarantee	GTEE	Dichotomous	0 = Personal guarantee; 1 = Secured loan	+
Interest rate	INT_RATE	Numerical	Monthly interest rate applied	+
Analyst's forecast	FORECAST	Dichotomous	MFI forecast until full repayment: 0 = No issues expected; 1 = Possible issues	+
			SYSTEMIC VARIABLES	
Real GDP	GDP	Numerical	Annual variation in GDP (%).	-
Unemployment rate	UNEMPT	Numerical	Annual variation in national annual unemployment (%)	+
General stock exchange index	COLCAP	Numerical	Annual variation in national stock exchange Index (%)	-
Exchange rate	EX_RATE	Numerical	Annual variation in exchange rate (%)	+

informal than those considered by traditional banks; and (b) recent literature concludes that the inclusion of qualitative variables improves the prediction power of models. With respect to the dependent variable, default of the microcredit, this takes a value of 1 if the microcredit fails, and 0 otherwise.

Idiosyncratic variables

As shown in Table 1, the idiosyncratic variables, specific to each borrower in the microcredit portfolio, are classified into non-financial variables (specific to the client), financial ratios (specific to the MFI) and loan variables (specific to the loan provided), following Lara-Rubio, Blanco-Oliver, and Pino-Mejías (2017), Blanco-Oliver, Irimia-Dieguez, and Oliver-Alfonso (2016) and Irimia-Dieguez, Blanco-Oliver, and Vazquez-Cueto (2015).

With respect to non-financial variables, it is generally accepted that women present a lower PD, according to credit scoring models (Zeballos, Cassar, and Wydick 2014; Blanco et al. 2013; Schreiner 2002), which are now commonly applied in studies of microfinance. Among the MFIs analysed in our study, women constitute a significant proportion of the lenders' clients, as evidenced in the study of Abdullah and Quayes (2016). Accordingly, we expect to obtain a negative sign for the *Gender* variable in our model. Zeballos, Cassar, and Wydick (2014) also consider *Marital status* to be a relevant idiosyncratic factor. In addition, Beisland, Déspallier, and Mersland (2019) and

Cozarenco and Szafarz (2018) have observed that responsibility and dependability within the financial system are fostered by the existence of a solid family nucleus. For this reason, we expect to obtain a negative sign for this variable, reflecting the fact that clients who form part of a stable family unit present a lower PD.

According to Blanco et al. (2013), Rayo, Lara, and Camino (2010) and Boyes, Hoffman, and Low (1989), the client's *Age* when the loan is granted can also influence PD. In the present study, a numerical variable is assigned to this variable, and a positive sign is expected, reflecting the belief that younger clients have greater potential than older ones, vis-à-vis business success, and hence are more likely to meet their repayment obligations.

The borrower's area of business activity (*Sector*) might also influence the probability of default (Cubiles-de-la-Vega et al. 2013; Van Gool et al. 2012; Schreiner 2004). However, our own research findings do not allow us to take a position in this respect.

Gutiérrez-Nieto, Serrano-Cinca, and Camón-Cala (2016) and Rayo, Lara, and Camino (2010) both concluded that clients living in urban areas are more likely to repay their debts than those living in more depressed, rural areas with little access to MFI. Therefore, we expect to obtain a negative sign for the *Zone* variable, as both of the MFIs examined mainly operate in cities.

Van Gool et al. (2012) and Dihn and Kleimeier (2007) analysed the employment situation (*Empt_Sit*) of the client as a factor that may influence the PD of microcredit clients. In this respect, Rayo, Lara, and Camino (2010) concluded that clients with experience in managing a microenterprise, as owners, are less likely to default on the loan, while Newman, Schwarz, and Borgia (2014) observed that the existence of support and commercial interaction between the MFI and its clients improves the commercial results of microenterprises. In view of these considerations, we expect to obtain a negative sign for the corresponding estimator.

According to Lin, Li, and Zheng (2017) and Elloumi and Kammoun (2013), the risk of default is reduced when MFI clients have a higher level of education, and therefore we expect to obtain a negative sign for the *Education* estimator.

Another factor that has been considered in this context is that of the duration of the client-MFI relationship (the *History* estimator) (Blanco et al. 2013; Gutiérrez-Nieto, Serrano-Cinca, and Camón-Cala 2016), as the persistence of an association between the client and the MFI generates knowledge, rapport and trust between the parties. Accordingly, we expect to obtain a negative sign for this estimator, indicating that long-term clients are more likely to discharge their loans correctly and on time; hence, PD is lower.

Blanco et al. (2013) and Rayo, Lara, and Camino (2010) took into account an indicator of the client's financial health, or creditworthiness, from the MFI perspective and defined *Cr-Wth* according to four categories: normal, some issues, weak, and doubtful. A borrower with no financial problems is expected to have a lower PD, and so this estimator has a positive sign.

When client information is consulted in the MFI credit record, then in addition to bank risks, consideration of the loan variables – loans approved, loan applications rejected, payment delays and average arrears – can help predict the probability that a client will default on a new loan. With respect to the first variable, a prior history of microfinance loans is indicative of pre-existing confidence in the client's creditworthiness (Gutiérrez-Nieto, Serrano-Cinca, and Camón-Cala 2016; Rayo, Lara, and Camino 2010), and so we expect to obtain a negative sign for this estimator. The other variables considered in this regard are indicative of any delinquency and financial difficulties recorded in the client's credit history, and their significance has been corroborated in previous research (Lara-Rubio, Blanco-Oliver, and Pino-Mejías 2017; Blanco et al. 2013).

Another question is that of the financial ratios considered. The difficulty encountered by MFIs in conducting an economic and financial assessment of their clients (Mester 1997; Schreiner 2002; Rayo, Lara, and Camino 2010) is reflected in the paucity of financial ratios with which to identify factors influencing the PD of a microcredit client. In recent years, however, these difficulties have to some extent been overcome, enabling MFIs to incorporate basic information about borrowers' liquidity, solvency, equity and profitability into their credit histories. The present study includes seven financial ratios that represent economic and financial strength and are widely employed in the banking industry to measure and control credit risk.

The first of these ratios, *R1*, indicates the number of days it takes for the client's business to recover its cash flow. The higher the value of this variable, the less likely the client will be able to meet the payment obligations (Blanco et al. 2013).

The *R2* ratio, between the gross income and the operating costs of the business, reflects its productivity and the degree of consolidation within the income statement. We expect to obtain a negative sign for this estimator.

With respect to the *R3* indicator of liquidity (payment capacity/total liquid assets), in microfinance the higher the immediate solvency ratio of the business, the lower the PD, and so we expect to obtain a negative sign for this estimator (Blanco et al. 2013).

In a similar fashion, the *R4* and *R5* ratios measure the firm's level of indebtedness and leverage, respectively, reflecting the weight of borrowing on its financial structure. In microfinance, borrowers are especially sensitive to the volume of debt, and the corresponding risk of bankruptcy, and therefore we expect to obtain a positive sign for each of these estimators.

The profitability ratios *R6 (Asset return*) and *R7 (Equity return)* measure the benefits obtained in relation to the assets and equity employed, respectively. These financial ratios are widely used in the analysis of financial risk, and Cubiles-de-la-Vega et al. (2013), Blanco et al. (2013) and Lara-Rubio, Blanco-Oliver, and Pino-Mejías (2017) all suggest a negative sign is to be expected, for both estimators.

Finally, with respect to loan-specific variables, *Amount* represents the nominal quantity of the loan or the amount granted in current currency. Previous research on credit scoring suggests that smaller loans are associated with a lower PD, in comparison with larger ones (Vogelgesang 2003; Viswanathan and Shanthi 2017), and so we expect to obtain a positive sign for this variable. Moreover, in line with Yang, Nie, and Zhang (2009) and Lieli and White (2010), we believe that a loan with a greater *Duratio*n, i.e. with greater uncertainty regarding repayment, would increase the PD, and so we expect to obtain a positive sign for this estimator.

Another variable that has been included in previous research is that of the intended *Purpose* of the loan obtained. Following Blanco et al. (2013) and Cubiles-de-la-Vega et al. (2013), we expect to obtain a negative sign for this estimator since the use of a greater volume of borrowed funds to acquire fixed assets might imply a greater PD.

In microfinance, *Guarantees* are usually required by the MFI when a borrower has defaulted previously (Maes and Reed 2012; Rayo, Lara, and Camino 2010). A positive sign for this estimator is expected. With respect to the *Interest* variable, a high rate would make debt repayment more onerous and therefore we expect to obtain a positive sign for this estimator (Vogelgesang 2003).

Finally, Cubiles-de-la-Vega et al. (2013) and Blanco et al. (2013) reported that the *Analyst's forecast*, although subjective, is a significant factor in determining microcredit risk since it reflects the personalized knowledge available to the MFI about the borrower. We expect to obtain a positive sign for this estimator.

Systemic variables

As explained in the first section, both the recommendations of international bodies and the conclusions of previous research (Navarro-Galera et al. 2017; Lara-Rubio, Blanco-Oliver, and Pino-Mejías 2017; Elgin and Uras 2013; Castro 2013) have highlighted the urgent current need to incorporate systemic factors into the analysis of default risk, thus improving on the traditional approach based on idiosyncratic factors alone. In this respect, variables such as *GDP* (real gross domestic product) and *COLCAP* (the main stock market index of the Colombia Stock Exchange) may exert a direct influence on PD (Shahriar and Garg 2017). Consequently, these factors are taken into account in our study, and are expected to have a negative sign in the corresponding estimators. Similarly, an increase in the unemployment rate (*UNEMPT*) would reduce income levels, thereby increasing PD, and so we assign a positive sign to this variable.

Finally, the exchange rate (*EX_RATE*) must be taken into account. A rise in the value of the local currency against the US dollar would increase PD, and vice versa, and so we expect to obtain a positive sign for this variable.

The macroeconomic variables under consideration are calculated through the following expression:

$$\Delta \mathbf{VM_{i,j}} = \frac{\mathbf{VM_{i+j}} - \mathbf{VM_i}}{\Delta \mathbf{VM_i}}$$

where:

$\Delta VM_{i,j}$: variation rate of the considered macroeconomic variable.

VM: considered macroeconomic variable.

i: moment of the granting of the loan.

j: microcredit duration.

III. Research methodology and experimental design

Artificial neural networks credit scoring models

Artificial Neural Networks ANNs emulate the neural activity in the human brain by transforming inputs into desired outputs using highly inter-connected networks of relatively simple processing elements, often termed neurons or nodes. Several theoretical results support a particular architecture, namely the multilayer perceptron (MLP), an example being the universal approximate property (Bishop 1995). Moreover, MLP is the most commonly used type of neural network in business studies (Zhang, Patuwo, and Hu 1998). An MLP is typically comprised of at least three different layers: an input layer, one or more hidden layers, and an output layer (Rumelhart, Hinton, and Williams 1986). The number of the nodes in the input layer corresponds to the number of independent variables, and the number of the nodes in the output layer to the number of dependent variables. However, the number of the hidden layers and the number of hidden layer nodes are more problematic to define. In the case of the number of the hidden layers, the universal approximation property of MLP state that one hidden-layer network is sufficient to model any complex system with any desired level of accuracy (Zhang, Patuwo, and Hu 1998), thus, all our MLPs will have only one hidden layer. With respect to number of hidden nodes, in accordance with Kim (2003), no general rule exists for the determination of this optimal number despite the fact that it constitutes a crucial parameter for the optimal network performance. The most common way to determine the size of the hidden layer is via experiments or trial and error. Following the above results, we have considered a three-layered perceptron where the output layer is formed of one node which provides the estimation of the probability of default.

Mathematically, the operation process of a MLP can be represented as follows. By denoting H as the size of the hidden layer, $\{v_{ih},\ i = 0,1,2, \ldots, p,\ h = 1,2, \ldots, H\}$ as the synaptic weights for the connections between the p-sized input and the hidden layer, and $\{w_h,\ h = 0,1,2, \ldots, H\}$ as the synaptic weights for the connections between the hidden nodes and the output node, then the output of the neural network from a vector of inputs $(x_1, \ldots, x_p)$ is:

$$\left(w_0 + \sum_{h=1}^{H} w_0 g\left(v_{0h} + \sum_{j=1}^{p} v_{ih} x_j \right) \right) \qquad (2)$$

with the logistic activation function $g(u) = e^u/(e^u+1)$, both in the hidden and output nodes. The output of this model provides an estimation of the probability of default for the corresponding input vector (as input nodes, all the MLP models use the set of variables selected for the LR model). A final decision can be obtained by comparing this output with a threshold, usually set at 0.5, thereby reaching a decision of default if $\hat{y} > 0.5$.

Two different programs are used in the construction of the MLP credit scoring models. The first choice is the freely available R system. The *nnet* R function (Venables and Ripley 2002) fits single- hidden-layer neural networks by means of the BFGS training algorithm in an effort to minimize an error criterion which allows a decay term λ to prevent overfitting problems[6]. For classification problems, one appropriate error function is the conditional maximum likelihood (or entropy) criterion (Hastie, Tibshirani, and Friedman 2009). Defining $W = (W_1, \ldots, W_M)$ as the vector of all M coefficients of the net, and given n targets $y_1, \ldots,$

y_n, where $y_i = 1$ for microcredit default, and $y_i = 0$ otherwise, the BFGS method is applied to the following problem:

$$\underset{W}{\mathrm{Min}} \sum_{n}^{i=1} \left(y_i \ln \hat{y}_i + (1 - y_i) \ln\left(1 - \hat{y}_i\right)\right) + \lambda \left(\sum_{M}^{i=1} W_i^2\right) \tag{3}$$

The R implementation of an MLP model requires the specification of two parameters: the size of the hidden layer (H) and the decay parameter (λ), and therefore a 10-fold cross-validated search of the size of the hidden layer (H) and the decay parameter (λ) is carried out over a grid defined as {1, 2, . . ., 20}x{0, 0.01, 0.05, 0.1, 0.2, . . ., 1.5}. In this case, we have also considered training without regularization, where $\lambda = 0$.

The Neural Network Toolbox (Demuth and Beale 1997) with MATLAB R2016b constitutes the other tool employed to fit MLP. This commercial system offers a great variety of learning rules, and we have considered the following six main learning algorithms to train the MLP: gradient descent, gradient descent with momentum, BFGS quasi-Newton (similar to R), Levenberg-Marquardt, scaled conjugate gradient, and resilient back-propagation. These learning rules try to minimize a sum of squared errors (SSE):

$$\underset{W}{\mathrm{Min}} \sum_{i=1}^{n} \left(y_i - \hat{y}_i\right)^2 \tag{4}$$

As in R, there remains the problem of selecting H, and therefore the size of the hidden layer (H) is chosen through a 10-fold cross-validation search in {1,2, . . ., 20} for each learning method.

The basic parameters of all the fitted MLP models are summarized in Table 2 below:

IRB model design

The main goal of the latest reform proposed by the Basel Committee on Banking Supervision (BCBS 2017) (Basel III) is that the capital requirements required for financial intermediaries should be more sensitive to the risk taken. To this end, Basel III enables banks to select one of two approaches for the determination of their capital requirements against credit risk: the standardized and the internal rating-based (IRB) approaches. In the standardized approach, the financial entities adopt fixed weighting of credit risk for each type of portfolio, thereby enabling the use of external rating provided by rating agencies. In contrast, under the IRB approach, the banks calculate their capital requirements for credit exposures using their own estimates of probability of default (PD) and of severity of loss given default (LGD). The principal contribution of this method is that calculates the maximum loss that a credit can produce (Value-at-Risk, VaR) with a 99.9% level of confidence. This maximum loss can, in turn, be broken down into two parts: expected loss (EL) which is covered with provisions, and unexpected loss (UL) for which capital (K) is required. The main disadvantage of the standardized approach is that it establishes fixed-risk weights for each type of portfolio independently of their risk. In contrast, with

Table 2. Basic parameters of multilayer perceptron models.

Models	Training Algorithm	Software	Hidden Nodes	Early Stopping	Regulari-zation	% Training	% Validation
MLP1	Gradient descent	Matlab	14	NO	NO	100	0
MLP2	Gradient descent	Matlab	14	YES	NO	75	25
MLP3	Gradient descent with momentum	Matlab	10	NO	NO	100	0
MLP4	Gradient descent with momentum	Matlab	10	YES	NO	75	25
MLP5	BFGS Quasi-Newton	Matlab	9	NO	NO	100	0
MLP6	BFGS Quasi-Newton	Matlab	9	YES	NO	75	25
MLP7	Levenberg-Marquardt	Matlab	2	NO	NO	100	0
MLP8	Levenberg-Marquardt	Matlab	2	YES	NO	75	25
MLP9	Scaled Conjugate Gradient	Matlab	14	NO	NO	100	0
MLP10	Scaled Conjugate Gradient	Matlab	14	YES	NO	75	25
MLP11	Resilient	Matlab	9	NO	NO	100	0
MLP12	Resilient	Matlab	9	YES	NO	75	25
MLP13	BFGS Quasi-Newton	R	10, $\lambda = 0$	NO	NO	100	0
MLP14	BFGS Quasi-Newton	R	3, $\lambda = 0{,}2$	NO	YES	100	0

the adoption of the IRB approach, the financial intermediaries determine their capital requirements through a more risk-sensitive way and interest rates are adjusted to the risk of each borrower. Despite the advantages of the IRB, the financial intermediaries have to first develop a credit-scoring model to estimate the probability of default (PD) of each borrower.

To estimate the capital requirement for a loan to be granted, Basel III considers a quartile of 99.9%, so that in assessing the capital required, 99.9% of the situations of the state of the economy that may influence a possible default by the customer are contemplated. The formula for the calculation of the capital requirement (K) is based on the portfolio risk model by Gordy (2003), where it is assumed that the capital required for each credit depends exclusively on credit-risk factors (PD and LGD) and not on the risk of the portfolio to which it belongs. In other words, the capital requirement for credit risk in retail operations, in accordance with Basel III rules, depends on the probability of default, on the loss given default, on the correlation coefficient of the borrower with the evolution of the economy, and on the 99.9% confidence level, as determined by Equation (6). The correlation coefficient, in turn, is a function of the default probability, and for this type of segment it lies between 0.03 and 0.16, according to:

$$K = f(PD, LGD, \rho, \alpha(99.9\%)) = \left[LGD \left(\frac{G(PD)}{\sqrt{(1-\rho(PD))}} + \sqrt{\frac{\rho(PD)}{1-\rho(PD)}}(0.999) \right) - PF.LGD \right] \quad (5)$$

$$\text{Correlation}\rho(PD) = 0.03 \cdot \frac{(1-e^{-35})}{(1-e^{-35})} + 0.16 \cdot \left(1 - \frac{(1-e^{-35})}{(1-e^{-35})} \right) \quad (6)$$

$$\text{RWA} = K \cdot 12.5 \quad (7)$$

where:

K: Capital requirements.

PD: Probability of default, obtained from credit scoring.

ρ (PD): Correlation coefficient.

LGD: Loss Given Default. Loss percentage or severity at the moment of default.

EAD: Exposure at Default.

RWA: Risk-Weighted Assets. EL: Expected Loss.

G (0.999): Inverse of the Distribution Function Normally accumulated = - 3.090.

G (*PD*): Inverse of the Distribution Function Normally accumulated in *PD*.

Figure 1 shows the calculative methodology of the interest rate, which should be negotiated with each borrower when considering the aim of obtaining the objective return on risk-adjusted capital (RORAC). Credit-scoring results influence the calculation of the risk premium, and hence it also has an effect on the determination of the interest rate of RORAC for each customer and on the profitability required of MFIs in their lending. The probability of default directly affects the amount of expected loss and indirectly affects the charge for unexpected losses through its influence on the calculation of risk capital.

The risk premium (Pr) is the sum of the two components, the risk premium derived from the expected loss (PrEL) and of the corresponding risk premium derived from the unexpected loss (PrUL). Furthermore, the expected loss is the result of multiplying the probability of default (PD) by the severity (LGD), and the unexpected loss is obtained from the product of multiplying the regulatory capital requirement (K) by the return on risk-adjusted capital in the sector (r), according to Equation (8).

$$\begin{pmatrix} RiskPremium \\ Pr \end{pmatrix} = \begin{pmatrix} Premiumfor \\ ExpectedLoss \\ PrEL \end{pmatrix} = \begin{pmatrix} Premiumfor \\ UnexpectedLoss \\ PrUL \end{pmatrix} = = (PD \cdot \text{LGD}) + (K \cdot \text{r}) \quad (8)$$

where:

EL: Expected Loss (covered with the provision)

UL: Unexpected Loss (covered with the capital requirement)

K: Capital requirement (Equation (5))

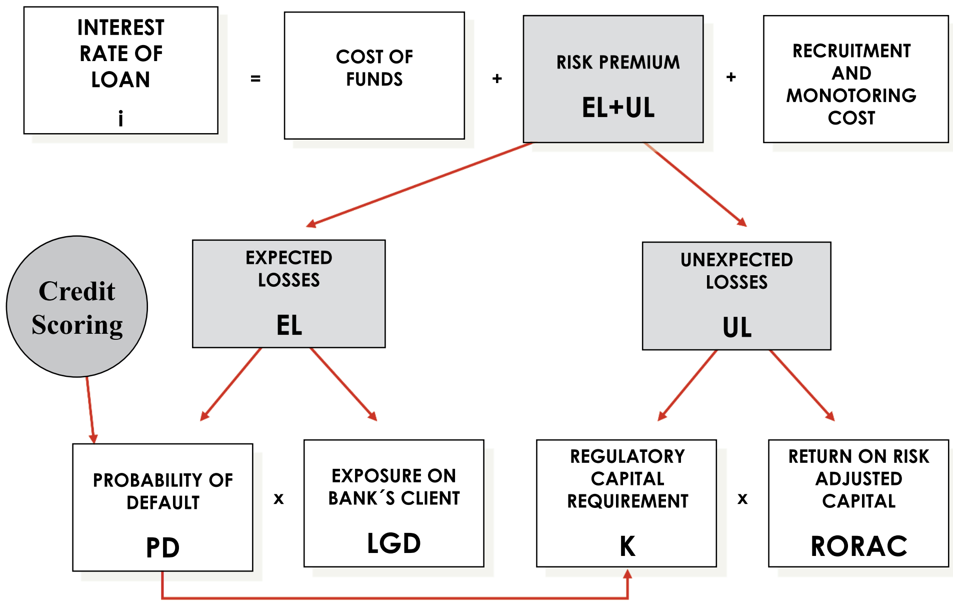

Figure 1. Calculation of interest rate adjusted to borrower risk.

r: Return on Risk-Adjusted Capital for the sector.

Applying the standardized approach and the IRB approach as proposed by the norms on capital requirements of Basel III, we determine customer profitability after tax from the following expression:

$$\text{RORAC} = \frac{(\text{FR} - \text{FC} - \text{OC} - \text{EL} + \text{IC}) \times (1 - \text{TR})}{\text{K}} \quad (9)$$

$$\text{FR} = \text{EAD} \times \text{IR} \quad (10)$$

$$\text{IC} = \text{K} \times \text{Rf} \quad (11)$$

where:

FR = Financial Revenue
FC = Financial Cost
OP = Operating Cost
EL = Expected Loss
IC = Income from Capital
K = Capital Requirement
TR = Tax Rate
EAD = Exposure at Default
IR: Interest Rate
Rf: Risk-free rate of interest, such as interest arising from government bonds

IV. Results and discussion

In this section, first the performance of the LR and MLPs are compared. Secondly, the results obtained in the IRB approach are shown and discussed, and the impact upon the management of the MFI is also analysed.

To evaluate the performance of the various credit-scoring models, the area under the ROC curve (AUC) is used. Furthermore, in accordance with West (2000), the expected misclassification cost (EMC) is also employed as performance criteria. Table 3 below contains the AUC, Type I–II

Table 3. AUC, Type I–II errors, and misclassification costs in the test sample.

MODELS	AUC	Type I Errors	Type II Errors	Misclassification costs
LR (*glm*)	0.9322	5.94%	20.96%	0.5715
MLP 1	0.9023	9.40%	24.40%	0.6772
MLP 2	0.9124	8.20%	22.90%	0.6326
MLP 3	0.9015	15.30%	21.50%	0.6305
MLP 4	0.9458	7.60%	16.70%	0.4691
MLP 5	0.9079	11%	15.70%	0.4597
MLP 6	0.9427	7.60%	17.10%	0.4795
MLP 7	0.9389	4.40%	22.40%	0.6014
MLP 8	0.9413	3.70%	22.40%	0.5980
MLP 9	0.9148	12.60%	18.30%	0.5347
MLP 10	0.9459	7.60%	16.70%	0.4692
MLP 11	0.9395	10.70%	15.30%	0.4478
MLP 12	0.9357	8.50%	17.60%	0.4968
MLP 13	0.9236	6.68%	22.81%	0.6230
MLP 14	0.9543	7.76%	15.30%	0.4337

errors and EMC[3] of all the models built. As can be observed in this table, the AUC of the LR[4] analysis is 93.22%, which is outperformed by the several MLP-based models (MLP number 4, 6, 7, 8, 10, 11, and 14). Substantial differences between LR and MLP methods are obtained in terms of the EMC criteria. Specifically, the improvement introduced by the best MLP model, (MLP 14), with respect to the classic LR method is 13.78% in terms of EMC. That is, the implementation of neural network approach reduces the MFI losses significantly, and therefore provides a way to obtain a competitive advantage over other MFIs, which fail to implement this methodology. Therefore, we conclude, in line with other authors (for example, see Ince and Aktan 2009), that, in general, not only do MLP models have a greater AUC but they also incur lower EMC than the traditional LR approach. These empirical results confirm the theoretical superiority (principally, non-linear and non-parametric adaptive-learning properties) of the MLP models over the parametric and widely used LR model to predict the default. Thus, we suggest that MFIs should use MLP models instead of the traditional and parametric LR, since a mere 1% improvement in accuracy would reduce losses in a large loan portfolio and save millions of dollars (West 2000).

With respect to the results obtained in the IRB approach, the previous Sections suggest that the accuracy performance of the credit-scoring models influence the pricing policy of the MFIs. In this sense, Table 4 gives the calculation of the risk premium of the microcredit portfolio, broken down into expected loss and capital requirements for the standardized approach and for the IRB approach with probabilities of default obtained via LR and MLP-based models. As shown in this table, the IRB approach based on MLP credit-scoring models benefit the MFI both in terms of capital requirements and expected loss in comparison with applying the LR method and Basel II standardized approach (BCBS 2006)

Table 4. Risk premium of credit-scoring models.

PRICING APPROACH	EXPECTED LOSS (EL)	CAPITAL REQUIREMENT (UL)	VaR (99.9%)
STANDARDIZED	$688,385.67	$360,303.36	$1,048,689.03
IRB – LR	$914,895.72	$173,793.66	$1,088,689.38
IRB – MLP	$913,426.19	$153,166.34	$1,066,592.52

Finally, we made a simulation of the interest rate that that the studied MFI should charge to their customers according to the IRB and standardized approaches. The data for this simulation were estimate according the following criteria. Firstly, a RORAC of 10.59%, which was estimated as an average ROE of the MFI, was considered for all microcredits. This information was collected from the MFI's financial indicators, which are published in the statistical section of the SBS. Secondly, the percentage of interest of each microcredit was calculated in such a way that the RORAC would be equal to 10.59%. Thirdly, we consider that the average annual real interest rate charged by the MFI to their borrowers in the period under review (38.44%) is a correct estimation of its current interest rate. The results of this simulation for the portfolio are presented in Figure 2. It can also be observed in this Figure 2 that the interest rate that the MFI would apply to the clients under the IRB approach, oscillate between 8.32% and 52.89%. In the case of implementing the standardized approach, this type of interest is, for all the portfolio clients and independent of their PD, at 18.16%. That is, under the IRB approach, the MFI charges each client a type of personalized interest in terms of their PD. To this end, the IRB approach is fairer on the clients and more efficient for the MFI since the clients with high PDs are charged a higher rate of interest than those borrowers whose PD are lower. The intersection of the expected rate of the IRB and the standardized approach is 20.38%. Therefore, all borrowers with PD lower than 40.61% will be charged a lower interest rate if the MFI applies the IRB approach than when it adopts the standardized approach (see Figure 2).

Therefore, in line with previous research carried out by Ruthenberg and Landskroner (2008), our results suggest that that whether the studied MFI adopted the Basel III IRB approach, then the high-quality customers would enjoy a reduction in loan interest rates, while the high-risk borrowers would

[3]In this study, the values selected for the calculation of the misclassification costs are: C_{21} = 1 and C_{12} = 5 (as recommended by West 2000); P_{21} and P_{12} are dependent of each model; and $\hat{\pi}_1 = 0.482$ and $\hat{\pi}_2 = 0.518$.

[4]The input variables selected in the sequential selection process, and the values of their coefficients for LR models are shown in Table A1 of Appendix A.

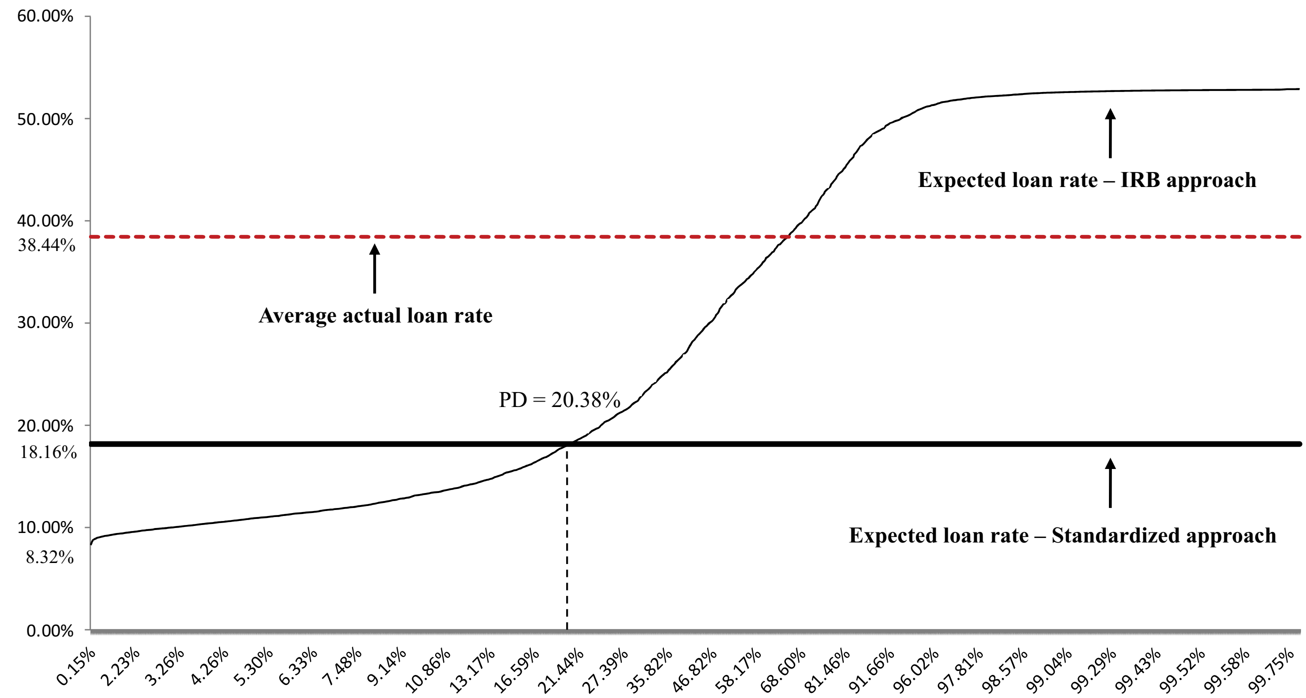

Figure 2. Average actual and expected loan rate.

benefit if the MFI adopted the standardized approach. Our findings suggest that the borrowers with PDs lower than 20.38% would benefit from the MFI applying the IRB approach, since the interest rate charged by the MFI would oscillate between 8.32% and 18.16%. In contrast, those customers with a PD higher than 20.38% would prefer the MFI to use the standardized approach since in this case the interest rate is fixed and equal to 18.16%. All these findings are in line with the results obtained by Ruthenberg and Landskroner (2008) in the case of the traditional bank industry. As can be observed in Figure 2, since the average actual interest rate charged to the customers by the MFI is of 38.44%, then all the borrowers would prefer the MFI to implement a credit-scoring system because it would provide the MFI with the opportunity to apply a pricing strategy and, thus, the MFI would reduce their particular interest rates.

V. Conclusions

This study explores the advantages for the MFIs linked to assignation of risk-adjusted interest rates for each applicant under the Basel III IRB approach in the microfinance industry.

Our findings provide three relevant conclusions. Firstly, the results suggest, in line with Ince and Aktan (2009) but in contrast with Bekhet and Kamel (2014), that multilayer-perceptron credit scoring not only offers performance of a higher accuracy but also incurs lower expected misclassification costs than the classic LR method for the microcredit framework. Exactly, the MLP provides a misclassification cost with a reduction of 13.78% in comparison with the LR model. These results promote the use of MLP credit-scoring models since these systems enable the MFIs to control and manage their portfolio credit risk more efficiently and professionally, by reducing the cost of credit analysis and losses due to failed borrowers, thereby enabling faster credit decisions, and through prioritization of repayment collection.

Secondly, we find that the implementation of an IRB approach with default probabilities obtained from MLP credit-scoring model produces the greatest benefits for the analysed MFI, in term of lower capital requirements and the best risk-adjusted interest rates. The reduction in the capital requirements for the MFI studied here is of over $200,000 on applying this model with respect to the standardized approach. And the decreases in the interest rates involved through the application of standardized and IRB approaches are of 20.28% and 30.12%, respectively, in comparison with actual interest rates charged by the studied MFI. With these substantial decreases in interest rates any MFI could increase its market share (even in an industry with negative growth rates) and compete on equal terms with its new competitors: the commercial banks. Moreover, with this reduction of microcredit interest rates, the number of microenterprises created by people on the base of a socioeconomic pyramid is increased, with all the positive implications carried with this increase for the social and economic development of these people and of their countries.

And thirdly, our empirical evidence suggests that, equal that occurs in the formal bank industry (Ruthenberg and Landskroner 2008), in the microfinance sector the IRB approach is also more risk- sensitive than the standardized approach. In this sense, the borrowers with PDs lower than 20.38% will benefit from IMF applying the IRB approach, since it oscillates the interest rate charged by MFI between 8.32% and 18.16%. In contrast, the customers with a PD higher than 20.38% will prefer the MFI to use the standardized approach, since in this case the interest rate is fixed and equal to 18.16%.

Based in these results, we suggest that MFIs apply an IRB approach with default probabilities obtained from an MLP credit-scoring model when setting up their credit-risk systems due to the fact that it produces the highest benefit for them in term of cutting credit losses, lower capital requirements and better risk-adjusted interest rates. This approach therefore provides a way for the MFIs to achieve a competitive advantage over their new competitors, commercial banks, in an increasingly constrained environment in which there is a strong emphasis on performing commercially sustainable operations without increasing the microcredit interest rates.

Disclosure statement

No potential conflict of interest was reported by the author(s).

ORCID

Juan Lara-Rubio http://orcid.org/0000-0001-7703-5920
Antonio Blanco-Oliver http://orcid.org/0000-0001-5540-692X

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Appendix A. Parametric statistical credit-scoring models: logistic regression

The coefficients and significance level of all the variables finally considered in the credit-scoring model based on the logistic regression are collected in Table A1. As shown in this table, all the slopes (signs) follow our theoretical expectations. The relevance of these most significant variables on the failure of micro-credits can be analysed by the absolute values of coefficients of each variable. Finally, the odds ratios measure the changes in odds when the predictor variable increases by 1 unit.

Table A1. Significant variables using logistic regression.

	B	S.E.	Wald	Sig.	Exp(B)
GENDER	-1.751	54.120	1.001	.074	0.174
CLIENT_HIS	-.069	2.878	3.573	.081	0.933
DELAY	.059	7.378	3.501	.036	1.061
ARREARS	4.496	92.489	.286	.025	89.639
R3	-.065	1.365	1.225	.000	.937
R4	.023	3.079	.578	.039	1.024
R7	-.042	3.016	3.000	.089	.959
AMOUNT	.270	36.921	2.536	.042	1.310
INT_RATE	4.037	18.926	.998	.048	56.638
GTEE	5.427	42.180	1.761	.090	227.562
FORECAST	5.513	27.166	.542	.041	247.894
COLCAP	-.104	10.335	2.301	.020	.901
Constant	-3.446	40.725	.666	.000	