A Social and Environmental Approach to Microfinance Credit Scoring

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Abstract

Microfinance institutions provide loans to low-income individuals. Their credit scoring systems, if they exist, are strictly financial. Although many institutions consider the social and environmental impact of their loans, they do not incorporate formal systems to estimate these social and environmental impacts. This paper proposes that their creditworthiness evaluations should be coherent with their social mission and, accordingly, should estimate the social and environmental impact of microcredit. Thus, a decision support system to facilitate microcredit granting is proposed using a multicriteria evaluation. The assessment of social impact is performed by calculating the Social Net Present Value. The system captures credit officers' experience and addresses incomplete and intangible information. The model has been tested in a microfinance institution. The paper shows how a small institution can include social and environmental issues in its decision-making systems to evaluate credit applications. A gap in the preferences was found between members of the board, who are socially driven, and managers and credit officers, who are financially drifted. This mission drift was corrected. The approach followed contributed to creating a culture of social and environmental assessment within the institution, especially among credit officers, thereby translating Microfinance institutions' social mission into numbers.

Keywords: microfinance, credit scoring, decision support system, social and environmental impact, multicriteria, social finance

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1. Introduction

Microfinance institutions (MFIs) provide microcredits—small loans not backed by collateral—to low-income individuals with poor or non-verifiable credit history. Like every loan, microcredits must be reimbursed. For this reason, MFIs must assess the financial aspects as well as the risks of the operation. The aim of credit scoring is to assess the creditworthiness of the applicant. Microfinance can be a profitable niche market (Campbell and Rogers, 2012); even commercial banks have downscaled to offer microcredits (Aggarwal, 2015). The social task performed by MFIs has no equivalent in commercial banking (Gutiérrez-Nieto et al., 2009). However, some MFIs are drifting from their mission, as highlighted by Armendáriz and Szafarz (2011), and instead act more like commercial banks. Many MFIs, however, have a clear social mission that is focused on alleviating poverty and making a social and environmental impact on the community. If social MFIs are to be coherent with their mission, their loan assessments should include not only financial aspects but also social and environmental aspects.

Few MFIs use credit scoring, and their assessments are based on the credit officer's experience and intuition (Van Gool et al., 2012; Baklouti and Baccar 2013). However, those MFIs using credit scores improve their performance (Bumacov et al. 2014). Several authors have reviewed the implementation of credit scoring in microfinance and conclude that MFIs using credit scoring do not take into account either social or environmental issues (Van Gool et al., 2012; Yu et al., 2015). The main determinants for loan allocation are related to the quality of the business projects, especially the expected probability of timely loan repayment (Sagamba et al., 2013; Hernandez and Torero, 2014). This is caused by the difficulty of integrating social and environmental aspects in credit scores, which are difficult to assess through a standardized procedure (Cornée and Szafarz, 2014). On the investor side, the United Nations Principles for Responsible Investment provide a framework for responsible investment in inclusive finance and affirm (1st principle), "we will incorporate Environmental, Social and Governance issues into investment analysis and decision-making processes" (United Nations, 2015).

In recent decades, risk management has gained importance in the microfinance sector. The Microfinance Workstream of the Basel Committee on Banking Supervision has developed guidance for the application of the core principles to microfinance activities (BIS, 2010). According to a study by the Centre for the Study of Financial Innovation, the two main threats for the microfinance industry are credit risk, worsened by the over-indebtedness of its clients, and the perception that the microfinance industry has lost sight of its social purpose (CSFI, 2012). Morduch (2011) claims that ‘we need to rethink microcredit’. The 2012 Microcredit Summit Campaign Report identifies credit risk as the main risk for the industry, followed by reputation risk (Maes and Reed, 2012). This motivates further research on the topic by developing a proposal to analyze both credit risk as well as the loss of MFI’ social purpose.

In a microcredit application, financial information is scarce because the applicants do not maintain accounting records (Ihua, 2009) and generally lack credit history (Dellien and Scheiner, 2005). They primarily think of how to survive the open market competition (Silajdžić et al., 2015). Bank credit scoring is based on statistical models, such as logistic regression (Wiginton, 1980), neural networks (West, 2000) or support vector machines (Baesens et al., 2003). Credit scoring databases, consisting of over 100,000 applicants measured on more than 100 variables, are quite common (Hand and Henley 1997). Statistical credit scoring implemented in microfinance, however, uses much smaller and simpler databases. For example, the database used by Blanco et al. (2013) contained financial data from 5,000 applicants. Bravo et al. (2013) used a logistic regression to develop a credit scoring model for microentrepreneus. There are also credit scoring developments for microfinance based on expert systems, which model the credit officer’s experience and do not require a large database (Schreiner, 2004). The previous microfinance credit scoring models, such as those developed by Viganò (1993), Aouam et al. (2009), Van Gool et al. (2012), Karlan and Zinman (2011), or Blanco et al. (2013) do not include social or environmental impact indicators. This paper proposes a social and environmental credit scoring, capitalizing on analogous practices such as those used in social audits (Osborne and Ball, 2010), social rating (Wilburn and Wilburn, 2014), social reporting (Gray et al., 1987) or sustainability reporting (Hahn and Kühnen. 2013). The design of a social and environmental credit scoring for microfinance and its application in a Colombian MFI is the main contribution of this paper.

When incorporating social and environmental aspects into a credit scoring, many conceptual problems arise. The lack of sufficient social and environmental data makes it difficult to use conventional statistical tools. Social finance entities have different priorities depending on their mission. Some of them are concerned with empowering women, whereas others are concerned with rural development, employment, or environmental development. The specific mix of priorities for each entity should be reflected in the design of a social and environmental credit scoring model. Multicriteria evaluation can help to model MFI preferences, and this paper suggests the use of the Analytic Hierarchy Process (AHP) by Saaty (1980), which can integrate social, technical or economic factors in complex decision making (Cziner et al., 2005). A microcredit application contains a variety of variables that are measured using different scales, which gives rise to another research question: how to address diverse information, including monetary, physical and qualitative data. The most challenging aspect of the model is how to value social impacts related to organizational aims (Munda, 2004). One possibility is to boil everything down to money by calculating the Social Net Present Value (SNPV) (Damigos, 2006) or the Social Return On Investment (SROI) (NEF, 2004 and Nicholls et al. 2009). This possibility, which is not without its challenges, is explored in this paper.

The decision-making model used in this paper has been tested in a socially oriented small MFI (2,590 active borrowers) in Colombia. The paper details the procedures followed, with the aim of ensuring that the model can be easily put into practice by other MFIs. One of the strengths of the model is its applicability. AHP has been successfully implemented in a diverse range of applications over the past 30 to 40 years (Saaty 2013), such as helping organizations to integrate environmental practices into their strategic plans (Sarkis, 2003) or evaluating the overall efficiency of a chemical engineering plant design, where environmental and safety regulations were also taken into account (Cziner et al., 2005). SROI is underused and undervalued due to practical barriers (Millar and Hall 2013). The procedure developed in the paper facilitates its applicability. The paper shows that a small MFI is able to include social and environmental issues in its decisional systems.

The rest of the paper is structured as follows. Section 2 analyzes credit scoring in microfinance. Section 3 describes the methods and approach of the proposed technique.

Section 4 presents the pilot testing of the model in a Colombian MFI. In the final section, the conclusions are presented and discussed.

2. Credit scoring in microfinance

Credit scoring comprises formal methods used to classify applicants for credit into ‘good’ and ‘bad’ risk classes (Hand and Henley, 1997). Credit scoring evaluations by conventional banks evaluate the applicant’s capacity to reimburse the loan principal and interest payments. Abdou and Pointon (2011), in a review of 214 studies on credit scoring, detail the variables used, the techniques applied and the performance evaluation criteria, finding that there is no overall best statistical technique used in building scoring models and affirming that the best technique for all circumstances does not yet exist.

In developed countries, there are credit bureaus that maintain excellent databases that can show, for example, if a client has not paid a simple utility bill. This type of information, however, is not always available for microcredit clients. Applicants generally do not have records regarding formal employment or a credit history. Furthermore, in the case of small companies, they often lack formal financial statements, and credit bureau data are not always available (BIS, 2010). MFIs work with data that is more costly and less predictive of risk than the data used by consumer lenders (Schreiner and Dellien, 2005). While microcredit clients do not usually have collateral (Vogelgesang, 2003), the industry has developed alternative systems to secure payments, such as solidarity groups (Morduch, 1999). Credit documentation is generated by the loan officer through informal collection of financial information via, for instance, visits to the borrower’s business and home (BIS, 2010). These features indicate that loan officers play a key role in microfinance credit evaluation.

Once the information has been captured, bank risk analysis departments calculate the default probability by analyzing aspects such as liquidity, solvency or profitability. While credit history is very important, loan purpose and loan return on investment (ROI) are also highly significant factors. The ROI is a key indicator, given the banks’ profit maximization target. However, the missions of social MFIs include social and environmental aims, such as poverty eradication or rural development. The traditional approach for credit scoring based on the identification of solvent and non-solvent clients is not sufficient for social MFIs. Because social MFIs seek to maximize outreach instead of profits (Armendáriz and Szafarz, 2011), the MFIs' model of credit scoring should incorporate such a social inclination.

Two approaches exist in credit scoring: statistical and judgmental (Hand and Henley, 1997). The statistical approach obtains the probability of default by using past loan information, while the judgmental approach is based on the expertise of credit analysts (Thomas, 2000). The judgmental approach is used when there is not enough data to develop a statistical credit score. As a consequence, microfinance institutions use it more frequently, by relying on the knowledge of their financial experts (Baklouti and Baccar, 2013). The two approaches are usually implemented as expert systems—that is, computer systems that emulate the abilities of a credit officer. The use of a given technique depends on the complexity of the institution and on the loan size and type (Malhotra and Malhotra, 2003).

Table 1 shows the main studies on microfinance credit scoring. Most of these studies are statistical, and they adapt scoring models of conventional banking. Because statistical models usually obtain high accuracy rates, they are preferred (Abdou and Pointon, 2011). However, with respect to this paper, because the aim is to develop a social and environmental microcredit scoring system, the judgmental approach is valuable. First, it is difficult to obtain a good database that contains sufficient social data. A credit scoring based on the experience of credit officers is easy to construct because a large database of past applications is not required (Berger and Black, 2011). The second strength of judgmental credit scoring is that credit officers today have a preeminent role in loan granting, and judgmental models are based on their experiences and intuitions (Baklouti and Baccar, 2013).

INSERT TABLE 1 ABOUT HERE

This paper suggests the use of AHP, a decision-making model that decomposes a complex multicriteria decision problem into a hierarchy (Saaty, 1980). This technique has been used for introducing social and environmental issues in decision making (Sarkis, 2003; Cziner et al., 2005). The basic procedure to carry out AHP consists of the following four steps: (1) modeling, (2) prioritization, (3) assessment and (4) synthesis (Saaty, 1980).

The first step organizes the business's objectives, criteria and alternatives into a hierarchy. The second step is the priority setting of the criteria by pairwise comparisons. For each pair of criteria, the decision maker is required to respond to a question such as, "How important is criterion A relative to criterion B?" Hence, a comparison matrix is obtained. The third step is calculating the relative weight of the factors using the comparison matrix. A consistency ratio is calculated to ensure that judgments are consistent. Further, the AHP algorithm produces weighted values for each alternative based on the judged importance of one alternative over another with respect to a common criterion.

AHP has been used by Aouam et al. (2009) to select and qualify potential borrowers. They propose a two-stage procedure that integrates both the judgmental and the statistical approaches. In the first stage, a benchmark based AHP is developed to represent subjective decisions based on the knowledge and experience of decision-makers. Once a potential borrower has been evaluated as eligible, the second stage applies a discriminant analysis model to classify the borrower as either possibly solvent or possibly insolvent. Che et al. (2010) used Fuzzy Analytical Hierarchy Process (FAHP) and Data Envelopment Analysis (DEA). FAHP was used for variable selection, and DEA was used to solve the decision problem. In this paper, AHP is used in a different way: to introduce the preferences regarding the MFI's social mission and to model those preferences. The proposal also includes the social and environmental impact valuation of the application. There is no clear method to assess the social impact, but according to Gibbon and Dey (2011), one of the most known and most often used is the Social Return on Investment (SROI) (Nicholls et al. 2009; REDF, 2001 and NEF, 2004). SROI attempts to quantify the social impact of an investment by expressing its social value in monetary terms using discounted cash-flow valuation, a well-established practice in financial analysis.

3. The model

Maes and Reed (2012) claim a loss of reputation in the microfinance sector because of the acute profit orientation among a number of MFIs. Morduch (2011) affirms that weak results in recent impact studies suggest the need to rethink microcredit. It can be argued that if MFIs want to recover their lost reputation, they must place greater emphasis on their social orientation. It is important that they introduce the social issue into the whole microfinance value chain. The social mission must guide the granting of microcredit. For this aim, not only is the financial information necessary, but the social and environmental information must also be gathered, as some MFIs are already doing. As well as analyzing the loan destination from a financial perspective, a method to qualify the social and environmental impact should be incorporated. Once the loan has been granted, expected repayments are scheduled and defaults are monitored. However, the social and environmental impact must also be monitored to verify whether the expected jobs were created or the environmental improvements were real. Credit rationing, meaning that loan applicants may not receive a loan even if they are willing to pay a high interest rate, increases considerably in economic downturns (Tedeschi et al, 2012). Even non-granted microcredits should be analyzed to identify the reasons for rejection and to propose solutions. For example, if an application is rejected because of the applicant's insufficient skills to run a business, the MFI can suggest training for the applicant or provide a partner in the business to compensate for the applicant's lack of ability. This is in line with Banerjee et al. (2015), who empirically found that the success of a microfinance program should be accompanied by full intervention, including training and coaching, health education and other aspects.

Figure 1 shows the process followed to develop the proposed microcredit scoring. The modeling stage adjusts the decisional model to the criteria set by the MFI. Later, MFI members express their preferences by means of pairwise comparisons among the proposed criteria. This step allows for the hierarchical priorities of the model to be obtained. The Decision Support System is then implemented. This can be performed by means of commercial software or by custom software. The AHP algorithm can even been implemented in a spreadsheet (Moreno et al., 2005). Loan applications, containing borrower information, are received by the MFI. The credit officer obtains the applicant's social and financial indicators, later performing the assessment of the different criteria. Finally, after multiplying the MFI's preferences with the analysts' assessments, partial scores are obtained for each criterion and each branch. The final score is obtained from these partial scores. The loan is accepted or denied. If the loan is denied, the applicant receives feedback for improving future loan applications.

INSERT FIGURE 1 ABOUT HERE

The first stage is modeling. The model has to include all the aspects that matter when granting social microcredits. Figure 2 shows the criteria included in the model. Each criterion has an associated set of measurable indicators that are tailored to each institution. The model is comprehensive because the three main branches contain information on the past (credit history), the present (applicant) and the future (loan destination). The *history branch* assesses past loans and their repayment patterns as well as information from external sources, such as other MFIs or suppliers. The *present branch* evaluates the scarce financial information available as well as intangible aspects of the applicant, such as the way his business is managed, or external aspects of the applicant's business. The *future branch* is based on project financial evaluations and social and environmental impact models. The list in Figure 2 is not exhaustive: it can be modified, as can the indicators used for each criterion. New branches can be easily added or removed. For example, an MFI focused on elderly borrowers would add a new branch to incorporate this criterion into the model. In addition, no more than seven criteria should be used in the pairwise comparison (Saaty and Ozdemir, 2003).

INSERT FIGURE 2 ABOUT HERE

The second stage is focused on reflecting the priorities of the MFI. The various MFIs have different social targets. The starting point for selecting the social criteria included in Figure 2 was the United Nations Millennium Development Goals, and the criteria chosen were impact on employment, impact on education, equal opportunities and empowerment of women, community outreach, impact on health and impact on environment. The character of the MFI must be reflected, so MFI decision makers must reveal their preferences among the different social and environmental criteria by weighting the importance of each criterion. Different techniques can be used, one of which is the Analytic Hierarchy Process (AHP) by Saaty (1980). AHP enables subjective judgments among different criteria by means of pairwise comparisons. Decision makers express their opinions about the value of the selected criteria by considering one pairwise comparison at a time. For example, "I have a strong preference for impact on employment over impact on education". With regard to the six social and environmental impact criteria noted above, this process requires that 15 comparisons be conducted. AHP can also contribute to reaching consensus when the opinions of decision makers are not coherent. In this case, the preferences are aggregated by using the geometric mean. The results are displayed in a normalized comparison matrix. The consistency ratio is also calculated (Saaty, 1980). If this ratio is below 10%, the pairwise comparison matrix is considered to be sufficiently consistent. From the normalized matrix, the priority vector is obtained, which reveals the weights given to each social criterion by decision makers. This vector, which is the normalized Eigen vector of the matrix, can be calculated with a simple spreadsheet (see, for example, Kardi, 2006).

Another novel aspect is the assessment of the social and environmental impact. Well-established methods exist to analyze a project from the financial perspective. For example, the return of the project is estimated using the Net Present Value (NPV). The NPV is the present value of net cash flows generated by a project, and accordingly, this serves as an indicator of the value of the project. Expected income and expense for each period are discounted using a given interest rate. However, there is not a generally accepted social and environmental impact assessment method. One problem is that social and environmental impact information is measured using different scales (such as the number of jobs created) or is measured qualitatively and imprecisely (such as improvements in education). Measurements from different scales cannot be directly combined. A possible solution to this problem could be to capture the expected economic value of social and environmental benefits, monetize them, and calculate their NPV, which is then regarded as their Social Net Present Value (SNPV). The SROI is obtained by dividing the discounted cash flows by the initial investment (Emerson and Twersky, 1996).

Assigning economic values to issues such as gender equality, regional development or loss of biodiversity is a controversial topic. Major criticisms of the SNPV come from the subjectivity underlying social indicators, and accordingly, efforts should be made to use indicators that are as objective as possible, quantifying them according to official sources. Globalvaluexchange.org is a database of financial proxies specifically designed for informing SNPV analyses, which relies on contributions from real practitioners to measure economic, social and environmental impact. The objective of the database is to adopt a consistent approach to obtain indicators and financial valuations for social and environmental outcomes. For example, if the project based in Colombia is to generate a new job, this can be assessed in economic terms by considering that the minimum monthly wage in Colombia is 589,500 Colombian Pesos (COP), according to the National Administrative Department of Statistics, which provides data on economic activity, health services costs or training costs. To assess the environmental impact, the monetary value of savings on CO2 emissions can be calculated from emissions trade markets. Tax payments, which are relatively easy to estimate, can be considered as one of the community impact indicators.

Finally, in the same way that a conventional financial operation is evaluated, the loan term is considered by estimating annual cash flows and discounting these flows at a given interest rate. However, there is a long debate with respect to the appropriate interest rate for assessing social projects (Stiglitz, 1982). This is a controversial and largely debated issue (Stiglitz, 1982; Stern, 2007; Cooney and Lynch-Cerullo, 2014, and Barro, 2015). Calculating the financial return on investment is not the same that calculating the non-financial return on investment. The latter should consider aspects such as the degree of certainty that social impacts will occur. Stern (2007) justifies a near-zero social rate that has been criticized for being inconsistent with empirical evidence and theoretical reasoning (Barro, 2015). The tendency among researchers is to use the risk-free rate to discount social returns (Cooney and Lynch-Cerullo 2014), which was the option chosen here. In this paper, the SNPV is obtained by applying the well-known formula, $SNPV = \sum_{t=0}^{n} \mathrm{S}_t/(1+\mathrm{r})^t$, where S=Social Impact, r=discount rate, t=time, and n=number of periods.

Once the SNPV is obtained for all the social and environmental criteria, these SNPVs are multiplied by the weight given by the MFI decision makers. Through this step, the MFI utility function is incorporated into the decisional process. However, the use of AHP scales can minimize the problem of assigning monetary values: the financial analyst first calculates the SNPVs and later, with these monetary values and other information, can perform a qualitative assessment using a scale ranging from very negative social and environmental impact (-3) to very positive social and environmental impact (+3). This approach is reasonable and coherent with the rest of the model because the financial branch performs in exactly the same way—that is, the NPV is estimated, and then the analyst transforms it into a qualitative scale. This method is coherent with the way AHP makes the assessments (Wedley et al., 2001; Saaty, 2004). The result obtained can then be easily transformed into a new scale that is easy to interpret in much the same way as rating agencies do. A proposal for the social and environmental impact score would contain four categories: negative social –environmental- impact (D); low positive social –environmental- impact (C); medium positive social –environmental- impact (B); and high positive social –environmental- impact (A). Finally, it would be desirable for the microcredit granting process to incorporate, in addition to financial controls to supervise loan repayment, controls to supervise the achievement of expected social and environmental impacts.

The SNPV allows for the comparison of different projects, and financial analysts feel comfortable when using rates and returns to assess social and environmental impact. However, the price to obtain these quantitative data is high, as they are not free from subjectivity. If the NPV depends on the accomplishment of given hypotheses by using reliable accounting data, the SNPV incorporates social and environmental indicators, which are ambiguous. Sveiby and Armstrong (2004) warn that because all social measurement systems are open to manipulation, it is not possible to measure social phenomena with anything close to scientific accuracy. It is not advisable to use these indicators for external reporting because this can result in pure propaganda. However, the proposal of this paper addresses internal assessment, and the MFI does not need to deceive itself by exaggerating its social and environmental impact. On the contrary, by using this tool, the MFI can engage credit officers to promote the social mission of the MFI.

4. Pilot case

This section illustrates how to implement a social and environmental approach in microcredit scoring. The approach was tested in Fundesan, a Colombian MFI, with a clear social mission through microcredit granting. Fundesan is a small NGO with 2,590 active borrowers. The research team was looking for a social MFI that was non-mission drifted and non-profit oriented. Two common indicators to measure this are a low Average Loan Size (ALS) (Cull et al., 2007) and a low Effective Interest Rate (EIR) (Mendoza, 2011). MicroFinance Transparency (mftransparency.org) is an international organization that gathers information on credit products and the true prices paid by clients. According to this international microfinance database, the Fundesan EIR (19.4%) is one of the lowest in the Colombian microfinance sector. It is important to note that the Colombian Superintendence of Banking fixes a recommended microcredit EIR at the 35.63%, with a usury rate of 53.45%

being punishable by law. The Fundesan ALS is 991.3 USD per borrower. This is considered a small loan when considering that the Colombian GNI per capita ppp is 9,560 USD, according to the World Bank. To sum up, both the EIR and the ALS for Fundesan are among the lowest in the country.

Following the flowchart in Figure 1, the first stage was determining the priorities of the Fundesan's decision makers. They were divided into three groups: members of the board of trustees, managers and credit officers. The group of credit officers comprises four employees with different levels of knowledge in microfinance. In addition, there were three managers and two members of the board. There are two possibilities for aggregating the preferences within a group: perform collegiate decisions or aggregate preferences by using the geometric mean or similar measures. Having such a small group, the collegiate decisions method was chosen. Table 2 displays the weights assigned for each group to the main branches of the model. The table shows that the board considers its main priority to be the assessment of the project to be financed. This means that the future (63.33%) is more important than the present situation of the applicant (26.05%) or his past credit history (10.63%). The board's priorities indicate that they have a long-term vision but do not know the day-to-day workings of the organization. Regarding the present branches, intangible aspects are preferred (75%) to the accounting aspects (25%). Finally, regarding project branches, social and environmental impact (75%) is weighted more heavily than financial valuation (25%), which is coherent with their vision. However, when this mandate reaches managers, some bias appears. For managers, what matters is the present (63.33%), which is then followed by the past (26.05%) and, finally, by the future (10.62%). Among the present branches, managers prefer tangible aspects (75%) to intangible ones (25%). These preferences are coherent with their financial knowledge and skills, which again differ from the preferences indicated by the board. Managers do agree with the board in their preference for the social and environmental impact of the project over its financial aspects. The gap widens when credit officers reveal their preferences, as they prefer the present aspects (47.96%) and the credit history (40.55%) of the applicant to the future aspects, which weigh in at only 11.50%. As for the valuation of the present, credit officers agree with managers in weighing tangible aspects at 75% compared to 25% for intangible aspects. Finally, with respect to the project, credit officers strongly prioritize financial assessment (83.33%) over social and environmental assessment (16.67%). It is interesting to study if the gap between the members of the board, managers and credit officers is something common in the sector. These results are coherent with those obtained by Baklouti and Baccar (2013) on microfinance officers' preferences. Their findings show that officers prefer financial aspects to social aspects. Sagamba et al. (2013) studied the factors that matter for microloan officers, finding very little difference between the preferences of microloan officers of nonprofit and for-profit MFIs, which contrasts to the essence of the definition of microcredit.

INSERT TABLE 2 ABOUT HERE

Therefore, according to the preferences as revealed by the various decision makers, a clear gap appears between the board members, who established the mission of the MFI with a clear social vision, and the managers, who run the MFI and prefer the present and tangible aspects. The gap between board members and credit officers is even greater, as the credit officers' preferences resemble those of a commercial bank: credit history, financial factors and tangible aspects. Fundesan is an exemplary MFI, which does not suffer from mission drift. Even so, the first stage of the model reveals the presence of a gap in the process of granting microcredit, a finding that is not necessarily negative. The success of Fundesan is most likely based on a combination of board members with a sound social commitment and experienced loan officers, who have their feet on the ground and can provide the necessary pragmatism. In fact, most of the defaults are caused by over-indebted clients who borrow from several MFIs. This aspect belongs to the history branch, which was heavily weighted by credit officers. Over-indebtedness is currently considered one of the main risks for the microfinance sector, as many borrowers ask for multiple loans from different MFIs in the absence of shared credit bureau information (Maes and Reed, 2012).

Table 3 shows the preferences regarding the six social and environmental criteria. Calculations were based on the AHP technique. As an example, one of the paired comparisons is shown and reveals that the MFI has a "strong preference of impact on employment over education". After performing the 15 paired comparisons, the comparison matrix is obtained. The consistency ratio is 4.5%, which is under the 10% threshold (Saaty, 1980). Once the comparison matrix was normalized, the priority vector was obtained, revealing the weights awarded to each social impact. Notice that the impact on employment received the greatest weight, at 41%, while community outreach was given the second greatest weight, at 19.6%. Education, health and the environment are only marginally considered, receiving 10 to 12%, while equal opportunities accounts for only 6.1%.

INSERT TABLE 3 ABOUT HERE

Once the model has been adjusted, the preferences obtained, and the relevant indicators for each criterion selected, the next stage is the evaluation of a credit application. Financial evaluation, with respect to its specific indicators, is similar to that conducted by any commercial bank, although some limitations apply due to the nature of microfinance. This is not a secret, as Fundesan has a loan application form available on its webpage that lists all the information needed. Table 4 focuses on the social and environmental valuation of a loan application by a Fundesan client who wishes to formalize and enlarge its hawking business into a market stall.

INSERT TABLE 4 ABOUT HERE

The first row of Table 4 reveals the loan financial assessment. It is a 6,000,000 COP loan that is to be reimbursed in 36 installments of 216,500 COP. The MFI’s EIR is 19.4%, which coincides with the loan’s IRR. Table 4 also shows the loan’s social and environmental assessment. First, the social impact is described in a qualitative way, as reflected by the credit officer on the application form. As can be appreciated, the loan will generate a new part-time job; two people will improve their management skills; new taxes will be collected that benefit the community; and the environment will be slightly improved because of recycling practices that will be incorporated in the new market stall. The credit officer did not appreciate the impact on health or on diversity.

Quantitative information allows for the calculation of the SNPV by discounting the social and environmental cash flows. The rate was 3.0%, the risk-free discount rate taken from the Colombian Treasury Bonds. The new part-time job was quantified using the Colombian minimum wage. As for the impact on education, the loan would improve the management skills of two workers. This was quantified at 360,000 COP for the first year and

180,000 for the second year. For assessing community outreach, the tax and social security payments were calculated for the newly created part-time job. The environmental impact is low, 50,000 COP, according to the data from the Colombian National Recycling Survey.

After financial projections, the total SNPV was 13,516,778 COP. The Assessment column transforms the SNPV into a scale that ranges from -3 (very negative social and environmental impact) to +3 (very positive social and environmental impact). The Weight column reveals the weights from the priority vector in Table 3. The social and environmental score is derived from multiplying the weight by the assessment. In the case studied, the loan received a score of 1.13 (C level), which indicates medium positive social and environmental impact.

The model was useful for Fundesan. In fact, it is relevant that Fundesan has changed its mission since then. Now, they aim at "being recognized by the community as an organization devoted to the social, environmental and economic development of the country." The paper shows that even a small MFI is able to incorporate into its decisional systems the social issues expressed in its mission. Large banks can sign the Equator Principles, a risk-management framework voluntarily adopted by financial institutions for determining, assessing and managing environmental and social risk in projects (Equator Principles, 2006). There are also ethical banks aiming to achieve sustainable development of banking and finance, and green microfinance initiatives. Many factors can potentially influence the environmental orientation of MFIs, such as the need for differentiation, the location in countries particularly prone to environmental degradation, or the maturity of the institution (Allet and Hudon, 2013; Allet, 2014). P2P social lending platforms such as Kiva.org channel loans from social responsible lenders. These lenders may ask for tools to maximize the social outreach of their loans. A key aspect is transparency among the criteria used by the MFI. This way, borrowers can know the preferences of the different lenders, identifying beforehand those that better match their projects.

Social assessment is complex. If the assessment of something as tangible as real estate often suffers from overvaluation or undervaluation, assessing future intangible social and environmental aspects cannot be an exact science, and one can only aspire to obtain approximate assessments. The criteria analyzed in the paper are not the only possible ones: Regional, political, or human development aspects are important in loan granting (Beck et al

2004), and especially in microcredit granting (Fatoki and Smit, 2011). What is important is creating a culture of social and environmental assessment within the MFI, especially among credit officers. Facing a loan application, the social mission must be considered, and the staff has to think over the expected social and environmental impact of the project. A new culture of social and environmental impact assessment can develop. This would begin with new information-collecting practices, which would make available more borrowers' social information. As the MFI matures, social data collection will be refined and improved, and a Social Information System that fully incorporates the social and environmental issues in the MFI decision-making process can be developed. This information would be later analyzed, disclosed and audited. A future line of research could focus on the development of social credit scoring, for example, by studying the relationship between social outreach and the probability of default.

Conclusions

There is a perception that the microfinance industry has lost sight of its social purpose and instead gives priority to maximizing profits. Reputational risk is considered one of the main threats to social microfinance institutions, and some authors have suggested the need to rethink microcredit. This paper proposes that those MFIs with a strong social mission could balance this negative trend by adopting Information Systems that incorporate the social mission of the MFI into the entire microcredit value chain. One of the aspects would be estimating the social and environmental impact of each microcredit granted as a part of the MFI credit scoring system.

Most MFIs do not capture the basic data that allow for identifying the relevant social and environmental variables to perform a statistical credit scoring. For this reason, an expert system, based on judgment, was chosen. Credit officers have a preeminent role in granting microloans, and judgmental models are based on their experience and intuition. The proposed model is comprehensive in that it includes all the possible criteria in microcredit valuation. The model is flexible because it allows criteria or indicators to be added or replaced, thus allowing it to be coherent with any social mission. The model can be applied to different contexts and countries by simply changing the model's preferences or weights. To this aim, the Analytic Hierarchy Process (AHP) was selected, and a weight for each social or environmental criterion was obtained.

The model can address various indicators, including qualitative and quantitative, social and financial, and even indicators measured on different scales. There is not a generally accepted method for social impact assessment. A simplified approach to the Social Net Present Value (SNPV) was chosen. The SNPV estimates the economic value of social and environmental benefits by monetizing those benefits and then calculating the present value of net cash flows generated by the project. In this way, an assessment of each social criterion is obtained. Finally, by multiplying the obtained assessment for the weight given by the MFI, a score is obtained, which then categorizes the social and environmental impact of the MFI into four categories: negative social and environmental impact (D); low positive social and environmental impact (C); medium positive social and environmental impact (B); and high positive social and environmental impact (A).

This decision-making model for granting social microcredit has been tested in a Colombian MFI, Fundesan. The paper illustrates the case of a loan application and describes how the system works. Every social assessment is complex and is not far from subjectivity. The estimation of future social and environmental impacts increases this difficulty. However, much can be gained from social assessment processes, as they can contribute to including social and environmental issues in the decision-making systems of the organization. The paper shows that even a small MFI is able to incorporate the social issues expressed in its mission into its decisional systems. It contributes to creating a culture of social and environmental assessment within the institution, especially among the credit officers, translating institutions' social mission into numbers. In fact, a gap was detected in the preferences between members of the board, who are driven by social and intangible aspects, and managers and credit officers, who are drifted to financial and tangible aspects. This situation was changing the course of the MFI. The gap has been corrected thanks to the use of the approach proposed, and now the MFI is staying on its intended course.

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Author	Country	Type	Description
Viganò (1993)	Burkina Faso	Individual	Discriminant Analysis. It analyzes applicant characteristics, business characteristics and loan characteristics.
Sharma and Zeller (1997)	Bangladesh	Group	Tobit Regression. It analyzes group characteristics (people, lands) and loan characteristics.
Zeller (1998)	Madagascar	Group	Tobit Regression. It analyzes group characteristics, microcredit program characteristics and community characteristics.
Reinke (1998)	South Africa	Individual	Probit Regression. It analyzes applicant characteristics, business characteristics and MFI branch characteristics.
Schreiner (1999)	Bolivia	Individual	Logistic Regression. It analyzes loan characteristics, applicant characteristics and credit officer experience.
Vogelgesang (2003)	Bolivia	Individual	Multinomial Logistic Regression. It analyzes applicant characteristics, business characteristics, loan characteristics and MFI characteristics.
Diallo (2006)	Mali	Individual	Discriminant Analysis and Logistic Regression. It analyzes credit history, applicant characteristics, business characteristics and credit officer experience.
Dinh and Kleimeier (2007)	Vietnam	Individual	Logistic Regression. It analyzes loan characteristics, applicant characteristics and the applicant’s relationship with the MFI.
Deininger and Liu (2009)	India	Group	Tobit Regression. It analyzes loan characteristics, applicant characteristics and business practices of community organizations.
Aouam et al. (2009)	Morocco	Individual	Analytic Hierarchy Process (AHP) and Discriminant Analysis. AHP is used to select and classify potential borrowers. Discriminant Analysis is used to classify the borrower as solvent or insolvent. It analyzes financial variables and commune size.
Che et al. (2010)	Taiwan	Individual	Fuzzy Analytical Hierarchy Process (FAHP) and Data Envelopment Analysis (DEA). FAHP is used for variable selection, and DEA is used to solve the decisional problem. It analyzes data on solvency, management, and risk of the applicant.
Van Gool et al. (2012)	Bosnia	Individual	Logistic Regression. It analyzes applicant characteristics, loan characteristics, and branch and credit officer characteristics.
Kinda and Achonu (2012)	Senegal	Individual	Logistic Regression. It analyzes applicant socio-economic characteristics, loan characteristics and credit officer experience.
Blanco et al. (2013)	Peru	Individual	Neural Networks. It analyzes historic data, collateral, applicant characteristics, business characteristics and macroeconomic variables.

Table 1. Studies on microfinance credit scoring.

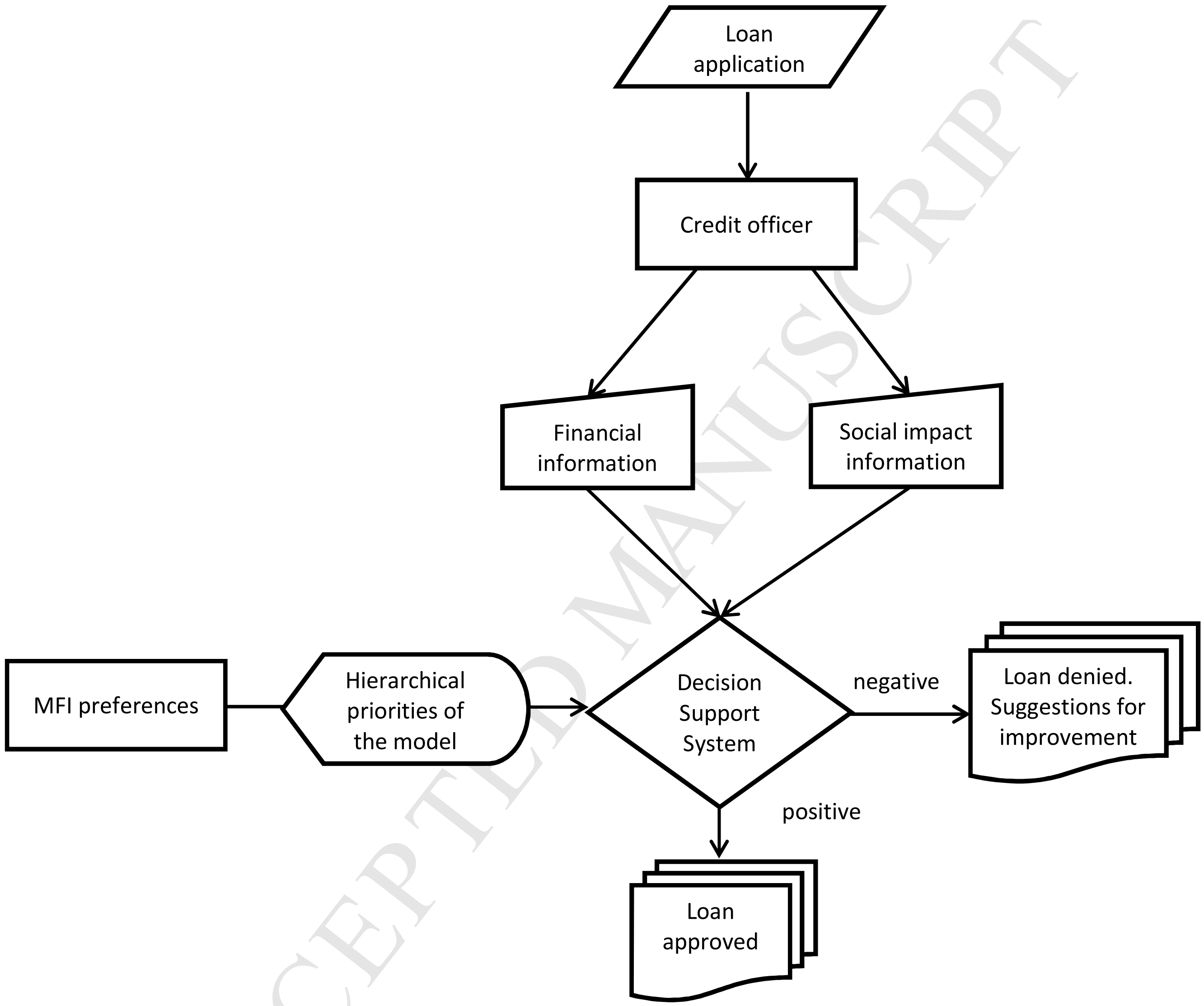

Figure 1. Flowchart of the social and environmental microcredit scoring decisional process. The model includes financial assessment and social impact assessment.

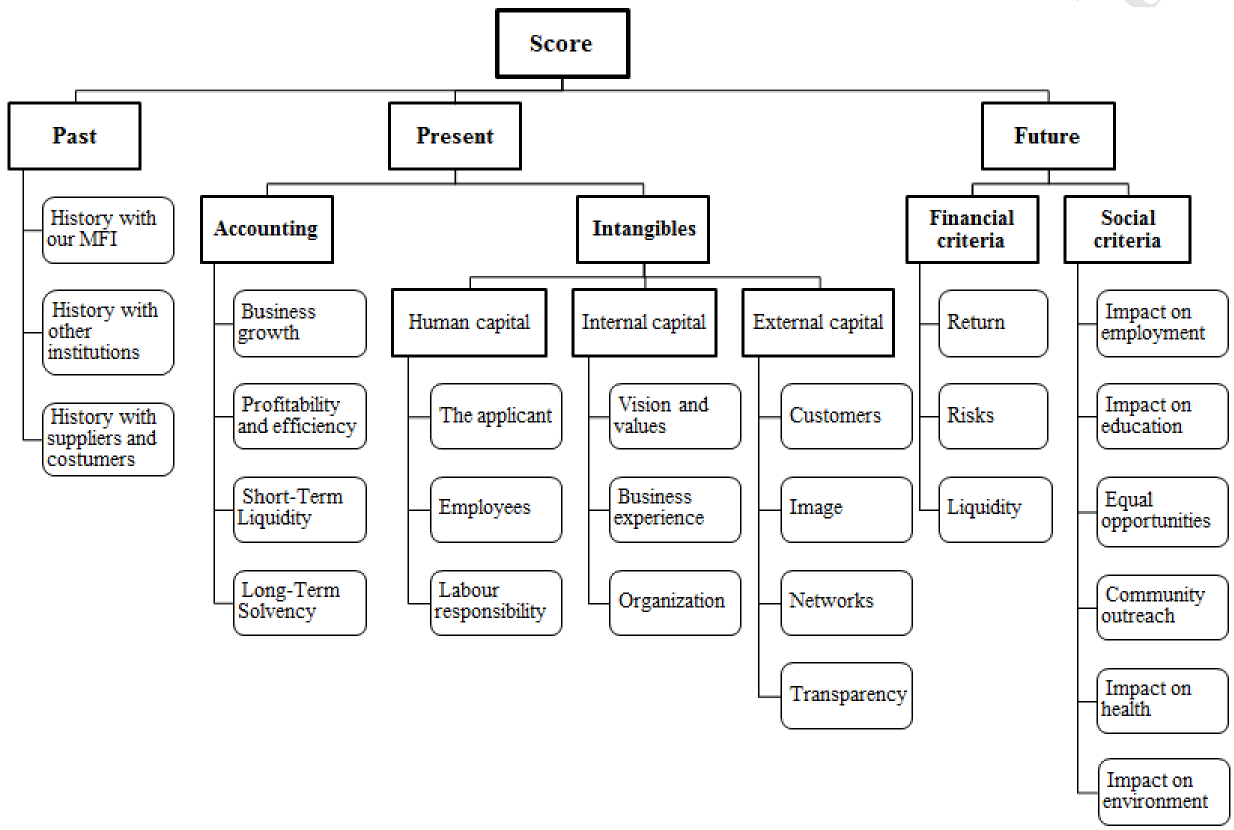

Figure 2. The figure shows the criteria included in the model with its branches and sub-branches. Each criterion has an associated set of measurable indicators that could be tailored to each institution.

Criteria	Board	Managers	Credit officers
Past (credit history)	**10.62%**	**26.05%**	**40.55%**
Present (the applicant)	**26.05%**	**63.33%**	**47.96%**
Accounting data	25%	75%	75%
Intangible	75%	25%	25%
Future (the project)	**63.33%**	**10.62%**	**11.50%**
Financial criteria	25%	25%	83.33%
Social and environmental impact	75%	75%	16.67%

Table 2. Preferences revealed by the three groups of decision makers (board, managers and credit officers) from the analyzed MFI.

An example of paired comparison:

Extreme preference of impact on employment over impact on education		Very strong		**Strong**		Moderate		Equal preference		Moderate		Strong		Very strong		Extreme preference of impact on education over impact on employment
9	8	7	6	5	4	3	2	1	1/2	1/3	1/4	1/5	1/6	1/7	1/8	1/9

Comparison matrix:

	Employ	*Education*	*Equality*	*Outreach*	*Health*	*Environment*
Impact on employment	1	**5**	3	3	4	4
Impact on education	1/5	1	2	1/2	1	2
Equal opportunities	1/3	1/2	1	1/4	1/3	1/3
Community outreach	1/3	2	4	1	2	2
Impact on health	1/4	1	3	1/2	1	1
Impact on environment	1/4	1/2	3	1/2	1	1
TOTAL	2.37	9.75	16.00	5.75	9.33	10.33

Normalized matrix:

	Employ	*Education*	*Equality*	*Outreach*	*Health*	*Environment*	*TOTAL*	*Weights*
Impact on employment	0.42	0.51	0.19	0.52	0.43	0.39	2.46	41.0%
Impact on education	0.08	0.10	0.13	0.09	0.11	0.19	0.70	11.7%
Equal opportunities	0.14	0.05	0.06	0.04	0.04	0.03	0.37	6.1%
Community outreach	0.14	0.21	0.25	0.17	0.21	0.19	1.18	19.6%
Impact on health	0.11	0.10	0.19	0.09	0.11	0.10	0.69	11.4%
Impact on environment	0.11	0.03	0.19	0.09	0.11	0.10	0.61	10.2%
TOTAL	1	1	1	1	1	1	6	100%

Consistency ratio (CR): 4.53%

Table 3. MFI preferences regarding the six social and environmental criteria. The calculations are based on the AHP technique. The first part shows a paired comparison of the employment criterion over the education criterion, while the second part shows the comparison matrix. The third part shows the normalized matrix, the priority vector (Weights column) and the Consistency ratio.

Financial assessment:

	Loan	Year 1	Year 2	Year 3
Financial cash flows	- 6,000,000	2,598,000	2,598,000	2,598,000

IRR 19.40%

Social assessment:

		Year 1	Year 2	Year 3	Social NPV	Social Assessment	Weight	Score
Employment	A new part-time job will be created	3,537,000	3,537,000	3,537,000	10,004,798	2	41.0%	0.82
Education	Two people will improve their management skills	360,000	180,000	-	519,182	1	11.7%	0.12
Equality	Non-significant	-	-	-	-	0	6.1%	0
Outreach	Tax and social security contributions	1,008,045	1,008,045	1,008,045	2,851,368	1	19.6%	0.20
Health	Non-significant	-	-	-	-	0	11.4%	0
Environment	Some recycling practices	50,000	50,000	50,000	141,431	0	10.2%	0
TOTAL		4,955,045	4,755,045	4,595,045	13,516,778			1.13 C level

Table 4. Financial assessment calculates the Internal Rate of Return (IRR) from monthly installments using compound interest rate. Social and environmental assessment quantifies the impact of the six social and environmental criteria by calculating the Social Net Present Value (SNVP) discounted at 3%, the Colombian risk-free interest rate. The Social Assessment column transforms the SNVP into a scale, ranging from -3 (very negative social and environmental impact) to +3 (very positive social and environmental impact). The score, obtained by multiplying the weight obtained in Table 3 by its assessment, ranges from -3 (minimum score) to +3 (maximum score).

Highlights:

Most credit scoring systems for microfinance institutions are strictly financial.

The paper proposes a financial and social decision-making model to grant microcredits.

Multicriteria evaluation assesses the social and environmental impact of loans.

The assessment of social and environmental impact uses the Social Net Present Value.

The model addresses monetary, physical and qualitative indicators.