A Social Approach to Microfinance Credit Scoring

C. Serrano-Cinca, B. Gutiérrez-Nieto and N. M. Reyes

Microfinance Institutions (MFIs) provide loans to low income individuals. The credit scoring systems of MFIs, if they exist, are strictly financial. Although many MFIs consider the social impact of their loans, they do not incorporate formal systems to estimate this social impact. This paper proposes that their creditworthiness evaluations should be coherent with their social mission and should, accordingly, estimate the social impact of microcredit. Thus, a decision support system to facilitate microcredit granting is proposed, and multicriteria evaluation is used to translate MFI’s social mission into numbers. The assessment of social impact is performed by calculating the Social Net Present Value (SNPV). The system captures credit officers’ experience and addresses incomplete and intangible information. The model has been tested in a microfinance institution. The paper illustrates an example of its use in practice.

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

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A Social Approach to Microfinance Credit Scoring

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Abstract

Microfinance Institutions (MFIs) provide loans to low income individuals. The credit scoring systems of MFIs, if they exist, are strictly financial. Although many MFIs consider the social impact of their loans, they do not incorporate formal systems to estimate this social impact. This paper proposes that their creditworthiness evaluations should be coherent with their social mission and should, accordingly, estimate the social impact of microcredit. Thus, a decision support system to facilitate microcredit granting is proposed, and multicriteria evaluation is used to translate MFI’s social mission into numbers. The assessment of social impact is performed by calculating the Social Net Present Value (SNPV). The system captures credit officers’ experience and addresses incomplete and intangible information. The model has been tested in a microfinance institution. The paper illustrates an example of its use in practice.

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1. Introduction

Microfinance Institutions (MFIs) provide microcredits, small loans, to low income individuals. Like every loan, they must be reimbursed. For this reason, the MFI 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. Because it is a profitable niche market, some commercial banks have entered the microcredit business. Those banks apply conventional credit scoring systems that are specifically adapted to the nature of microfinance. Some MFIs are drifting from their mission, as highlighted by Armendáriz and Szafarz (2011), and act instead more like commercial banks. Many MFIs, however, have a clear social mission that is focused on alleviating poverty and achieving social impact in the community. In our opinion, if social MFIs are to be coherent with their mission, their loan assessments should not only include financial aspects but should also include social aspects. Nevertheless, few MFIs use credit scoring (Van Gool et al., 2012), and they are from having formalized systems that include social aspects of the loan.

Risk management has gained importance in the last decades 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, and both threats are explored here.

In a microcredit application, financial information is scarce because the applicants do not maintain bookkeeping (Ilhua, 2009), and they generally lack credit history (Dellien and Scheiner, 2005). 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 databases. For example, the database used by Blanco et al. (2013) contained financial data from 5,000 applicants. 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). To the best of our knowledge, the previous microfinance credit scoring models, such as Viganò (1993), Aouam et al. (2009), Van Gool et al. (2012), Karlan and Zinman (2011), or Blanco et al. (2013) do not include a social impact estimate or its assessment. This paper proposes a social credit scoring, the same way as there is social audit, (Osborne and Ball, 2010), social rating (Gutiérrez-Nieto and Serrano-Cinca, 2007), or social reporting (Gray et al., 1987). The design of a social credit scoring for microfinance and its application in a Colombian MFI is the main contribution of this paper.

When incorporating social aspects into a credit scoring, many conceptual problems arise. The lack of enough social data makes it difficult to use conventional statistical tools. Social finance entities have different priorities according to their mission. Some of them are concerned with women empowerment, whereas others are concerned with rural development, employment, or environmental development. This specific focus should be incorporated in the design of a social credit scoring model. As multicriteria evaluation can help to model MFI preferences, this paper suggests the use of the Analytic Hierarchy Process (AHP) by Saaty (1980). A microcredit application contains variables of different nature that are measured using different scales, which gives rise to another research question: how to address diverse information including monetary, non monetary and qualitative data. One possibility is to boil everything down to money by calculating the Social Net Present Value (SNPV) 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.

Because many social MFIs are small institutions, they cannot develop complex decisional systems. The decision-making model used herein has been tested in a socially oriented Colombian small MFI (2,590 active borrowers). The paper details the procedures followed, with the aim that the model can then be easily put into practice by other MFIs.

The rest of the paper is structured as follows. Section 2 analyzes credit scoring in microfinance. Section 3 describes the methodology 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 for classifying applicants for credit into ‘good’ and ‘bad’ risk classes; Hand and Henley (1997). Credit scoring evaluations by conventional banks evaluate the applicant capacity to reimburse the loan principal and interest payments. Abdou and Pointon (2011), in a review of 214 studies of credit scoring, detail the variables used, the techniques applied and the performance evaluation criteria.

In developed countries, there are credit bureaus and excellent databases that inform if a client has not paid a simple utility bill. This type of information, however, is not always available for microcredit clients. Applicants do not generally have records regarding formal employment or have a credit history. Furthermore, in the case of small companies, they do not report financial statements, BIS (2010). MFIs work with data 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. Loan documentation is generated by the loan officer through 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 departments calculate the default probability by analyzing aspects such as liquidity or solvency. While credit history is very important, the loan destination and its return on investment (ROI) is also a highly significant factor. The ROI is a key indicator given the banks’ profit maximization target. However, social MFIs have social aims in their missions, such as poverty eradication or rural development. In our opinion, the traditional approach for credit scoring based on the identification of solvent and non-solvent clients is not sufficient for social MFIs. As social MFIs maximize outreach instead of profits (Armendáriz and Szafarz, 2011), so the MFIs’ model of credit scoring should incorporate such social inclination.

Two approaches exist in credit scoring: statistical and judgmental. The statistical approach empirically analyzes data on past loans to predict the future behavior of the loan applicant (Hand and Henley, 1997). The judgmental approach is based on experience and beliefs of loan analysts (Thomas, 2000). The two approaches are usually implemented as expert systems; that is, computer systems that emulate credit officer's ability.
Table 1 shows the main studies on microfinance credit scoring. Most of the studies are statistical and they adapt conventional banking scoring models. As statistical models usually show high accuracy rates, they are preferred, Abdou and Pointon (2011). However, with respect to this paper, as the aim is to develop a social microcredit scoring system, the judgmental approach is determined to be valuable. First, it is difficult to obtain a good database that contains sufficient social data. A credit scoring based on credit officer experience is easy to construct because a large database of past applications is not required, see 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.

AHP has been used by Aouam et al. (2009) to select and qualify potential borrowers. They further use Discriminant Analysis to classify the borrower as solvent or 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. Our paper uses AHP in a different way: to extract the preferences regarding the MFI social mission and to model those preferences. Our proposal also includes the social impact valuation of the application. There is no clear methodology 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, by using discounted cash-flow valuation, a well-established practice in the 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 MFI s. Morduch (2011) affirms that weak results in recent impact studies suggest the need to rethink microcredit. In our opinion, if MFI s 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 information must also be gathered, as some MFIs are already doing. As well as analyzing the loan destination from the financial perspective, some methodology to quantify the social impact should be incorporated. Once the loan has been granted, expected repayments are scheduled, and defaults should be monitored. However, social impact must also be monitored to verify whether the expected jobs were created or the environmental improvements were real. Even non-granted microcredits should be analyzed to identify the reasons for rejection and to propose solutions. For example, in an application rejected because of the applicant’s insufficient skills to run its business, the MFI can suggest training for the applicant or providing a partner in the business to compensate for the applicant’s lack of abilities. Figure 1 shows the process to develop the proposed microcredit social scoring.

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Figure 1

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The first stage is modeling. The model has to include all the aspects that matter when granting social microcredit. This paper adapts a previous model that was applied to social venture capital, Serrano-Cinca and Gutiérrez-Nieto (2013). 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 behavior and also assesses 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 impact models.

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Figure 2

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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 women empowerment, 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 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 one single pairwise comparison at a time. For example, “I have a strong preference for impact on employment over impact on education”. In the case of the 6 social impact criteria, this indicates that 15 paired comparisons must 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 by decision makers to each social criterion. 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 impact. To analyze a project from the financial perspective, well-established methodologies do exist. 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. But there is not a generally accepted social impact assessment methodology. One problem is that social 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 benefits, monetizing those social benefits, and calculating 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).
Major criticisms to the SNPV come from the subjectivity underlying social indicators, and accordingly, efforts should be made to use indicators as objective as possible, quantifying them according to official sources. 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 Colombian minimum monthly wage 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 can be considered as one of the community impact indicators, which are reasonably easy to estimate.

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). We suggest using the Internal Rate of Return (IRR) of the loan. Accordingly, the SNPV is obtained by applying the well-known formula,  

\[ SNPV = \sum_{t=0}^{n} S_t / (1 + r)^t \]

where S=Social Impact, r=discount rate, t=time, and n=number of periods.

Once the SNPV is obtained for all the social criteria, we propose to multiply the SNPV by the weight given by MFI decision makers. In this way, the MFI utility function is incorporated within the decisional process. The result obtained can then be easily transformed into a scale that is easy to interpret in much the same way as rating agencies do. A proposal for the social impact score would contain four categories: negative social impact (D), low positive social impact (C), medium positive social impact (B) and high positive social impact (A). Finally, it would be desirable that the microcredit granting process incorporate, in addition to the financial controls to supervise loan repayment, the social controls to supervise the achievement of expected social impacts.

The SNPV allows for the comparison of different projects and financial analysts feel comfortable when using rates and returns to assess social 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 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 deals with internal assessment, and the MFI does not need self-deception by exaggerating its social impact. On the contrary, the MFI can engage credit officers, by using this tool, to promote the social mission of the MFI.

4. Pilot case

This section illustrates how to implement a social 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). We explored MicroFinance Transparency (mftransparency.org), 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 among 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 Average Loan Size (ALS) is 991.3 USD per borrower. This is considered a small loan when taking into account 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. 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 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 its past credit history (10.63%). Regarding the present branches, intangible aspects are preferred (75%) over the accounting aspects (25%). Finally, regarding project branches, social impact (75%) is weighted over financial valuation (25%). However, when this mandate reaches managers, some bias appears. For managers, what matters is not the future, but 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%) over intangible ones (25%), which again differs from the preferences indicated by the Board. Managers do agree with the Board in their preference for the social 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 over 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 assessment (16.67%)

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Table 2

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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 who 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 microcredit granting, 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 with experimented loan officers, having their foot on the ground, providing the necessary pragmatism. In fact, most of the defaults were caused by over-indebted clients, who borrow from several MFIs. This aspect belongs to the history branch, which was highly weighted by credit officers. Over-indebtedness is currently considered as one of the main risks for the microfinance sector, Maes and Reed (2012).

Table 3 shows the preferences regarding the six social 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 receives the greatest weight, at 41%, while community outreach accounts for 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%.

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, though some limitations apply, given the microfinance nature. This is not a secret as Fundesan has a loan application form available on its webpage that lists all of the requisite information. Table 4 focuses on the social valuation of a loan application by a Fundesan client who wishes to formalize and enlarge its hawking business into a market stall.

Table 4, in its first row, 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 IRR is 19.4%, which coincides with the loan’s EIR. Table 4 also shows the loan’s social 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 incorporated in the new market stall. The credit officer did not appreciate impact on health or on diversity.

Quantitative information permits the calculation of the Social Net Present Value (SNPV) by discounting the social cash flows using the 19.4% discount rate. 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 10,198,827 COP. The Assessment column transforms the SNPV into a scale that ranges from -3 (very negative social impact) to +3 (very positive social impact). The Weight column reveals the weights from the priority vector in Table 3. The social score is derived from multiplying the weight by the assessment, and it ranges from -3 (minimum score) to +3 (maximum score). In the case studied, the loan received a 1.13 social score, thus indicating medium positive social impact.

Social assessment is complex. If the assessment of something as tangible as a real state often suffers from overvaluation or undervaluation; assessing future intangible social aspects cannot be an exact science, and we can only aspire to obtain approximate assessments. In our opinion, what is important is to create a culture of social assessment within the MFI, especially among the credit officers. Facing a loan application, the social mission must be considered, and the staff has to think over the expected social impact of the project. As the MFI matures, social data collection will be refined and improved, and a Social Information System that fully incorporates the social issues in the MFI decision-making process can be developed.

Conclusions

There is a perception that the microfinance industry has lost sight of its social purpose, and instead gives priority to maximizing profits. The reputational risk is considered one of the main threats to social microfinance institutions, and some authors are suggesting 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 throughout the entire microcredit value chain. One of the aspects would be the estimation of the social impact of each microcredit granted as a part of the MFI credit scoring system.
Most MFIs do not capture the basic data that allow identifying the relevant social 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 microloan granting, 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 proposed model is also flexible in that it allows each MFI to adapt the model to its needs and priorities, thus making it coherent with its social mission. To this aim, the Analytic Hierarchy Process (AHP) was selected, and a weight for each social criterion was obtained.

The model can address various indicators including qualitative and quantitative, social and financial, and even indicators measured in different scales. There is not a generally accepted methodology for social impact assessment. A simplified approach to the Social Net Present Value (SNPV) has been chosen. The SNPV estimates the economic value of social 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 impact of the MFI into four categories: negative social impact (D), low positive social impact (C), medium positive social impact (B), and high positive social impact (A).

This decision-making model for social microcredit granting 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 impacts increases this difficulty. However, much can be gained from social assessment processes, as they can contribute to include social issues in the decision-making systems of the organization.

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**Table 1.** Microfinance credit scoring studies.
Figure 1. Flowchart of the social microcredit scoring decisional process. The model includes financial assessment and social impact assessment.
**Figure 2.** The model with its branches and sub-branches.
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<th>Board</th>
<th>Managers</th>
<th>Credit officers</th>
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<tr>
<td>Past (credit history)</td>
<td>10.62%</td>
<td>26.05%</td>
<td>40.55%</td>
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<tr>
<td>Present (the applicant)</td>
<td>26.05%</td>
<td>63.33%</td>
<td>47.96%</td>
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<tr>
<td>Future (the project)</td>
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<td>75%</td>
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<tr>
<td>Intangible</td>
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<tr>
<td>Future</td>
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<tr>
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</table>

Table 2. Revealed preferences of the three groups of decision makers from the analyzed MFI.
An example of paired comparison:

<table>
<thead>
<tr>
<th>Extreme preference</th>
<th>Very strong</th>
<th>Moderate</th>
<th>Equal preference</th>
<th>Very strong</th>
</tr>
</thead>
<tbody>
<tr>
<td>of impact on employment over education</td>
<td>9</td>
<td>8</td>
<td>7</td>
<td>6</td>
</tr>
<tr>
<td>Impact on employment</td>
<td>1</td>
<td>5</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>Impact on education</td>
<td>1/5</td>
<td>1</td>
<td>2</td>
<td>1/2</td>
</tr>
<tr>
<td>Equal opportunities</td>
<td>1/3</td>
<td>1/2</td>
<td>1</td>
<td>1/4</td>
</tr>
<tr>
<td>Community outreach</td>
<td>1/3</td>
<td>2</td>
<td>4</td>
<td>1/4</td>
</tr>
<tr>
<td>Impact on health</td>
<td>1/4</td>
<td>1</td>
<td>3</td>
<td>1/2</td>
</tr>
<tr>
<td>Impact on environment</td>
<td>1/4</td>
<td>1/2</td>
<td>3</td>
<td>1/2</td>
</tr>
<tr>
<td>TOTAL</td>
<td>2.37</td>
<td>9.75</td>
<td>16.00</td>
<td>5.75</td>
</tr>
</tbody>
</table>

Normalized matrix:

<table>
<thead>
<tr>
<th>Extreme preference</th>
<th>Very strong</th>
<th>Moderate</th>
<th>Equal preference</th>
<th>Very strong</th>
</tr>
</thead>
<tbody>
<tr>
<td>of impact on education over impact on employment</td>
<td>5</td>
<td>4</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>Impact on employment</td>
<td>0.42</td>
<td>0.51</td>
<td>0.19</td>
<td>0.52</td>
</tr>
<tr>
<td>Impact on education</td>
<td>0.08</td>
<td>0.10</td>
<td>0.13</td>
<td>0.09</td>
</tr>
<tr>
<td>Equal opportunities</td>
<td>0.14</td>
<td>0.05</td>
<td>0.06</td>
<td>0.04</td>
</tr>
<tr>
<td>Community outreach</td>
<td>0.14</td>
<td>0.21</td>
<td>0.25</td>
<td>0.17</td>
</tr>
<tr>
<td>Impact on health</td>
<td>0.11</td>
<td>0.10</td>
<td>0.19</td>
<td>0.09</td>
</tr>
<tr>
<td>Impact on environment</td>
<td>0.11</td>
<td>0.03</td>
<td>0.19</td>
<td>0.09</td>
</tr>
<tr>
<td>TOTAL</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Weights</td>
<td>6</td>
<td>100%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Consistency ratio (CR): 4.53%

Tabla 3. MFI preferences regarding the six social criteria. 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:

<table>
<thead>
<tr>
<th>Loan</th>
<th>Year 1</th>
<th>Year 2</th>
<th>Year 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>-6,000,000</td>
<td>2,598,000</td>
<td>2,598,000</td>
<td>2,598,000</td>
</tr>
</tbody>
</table>

IRR 19.40%

Social assessment:

<table>
<thead>
<tr>
<th>Year 1</th>
<th>Year 2</th>
<th>Year 3</th>
<th>Social NPV</th>
<th>Social Assessment</th>
<th>Weight</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Employment</td>
<td>A new part-time job will be created</td>
<td>3,537,000</td>
<td>3,537,000</td>
<td>3,537,000</td>
<td>7,521,197</td>
<td>2</td>
</tr>
<tr>
<td>Education</td>
<td>Two people will improve their management skills</td>
<td>360,000</td>
<td>180,000</td>
<td>-</td>
<td>427,767</td>
<td>1</td>
</tr>
<tr>
<td>Equality</td>
<td>Non-significant</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0</td>
</tr>
<tr>
<td>Outreach</td>
<td>Tax and social security contributions</td>
<td>1,008,045</td>
<td>1,008,045</td>
<td>1,008,045</td>
<td>2,143,541</td>
<td>1</td>
</tr>
<tr>
<td>Health</td>
<td>Non-significant</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0</td>
</tr>
<tr>
<td>Environment</td>
<td>Some recycling practices</td>
<td>50,000</td>
<td>50,000</td>
<td>50,000</td>
<td>106,322</td>
<td>0</td>
</tr>
<tr>
<td>TOTAL</td>
<td></td>
<td>4,955,045</td>
<td>4,755,045</td>
<td>4,595,045</td>
<td>10,198,827</td>
<td>1.13</td>
</tr>
</tbody>
</table>

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