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Title Page

Social performance considered within the global performance of Microfinance institutions: a new approach

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Abstract

In last years, microfinance has been seen as an effective measure for empowering whole nations or marginalized groups. However, some negative issues especially with respect to over-indebtedness and high interest rates have been discussed as well. In fact, the performance of Microfinance Institutions (MFIs) has traditionally been measured by ratios. Thus, it should be remembered that MFIs are special socially-oriented financial organizations, mainly interested in the economic development of both rural and urban areas, in creating jobs, incorporating women into the labour market and addressing environmental concerns. The activity and performance ratios of these organizations are usually based on a single criterion, generally related to financial aspects or the extent of their outreach, in such a way that the performance measurement can vary according to the criterion selected. This paper proposes a new approach, a multicriteria method based on goal programming that considers not only financial aspects and outreach, but also the social performance related to the activities of a group of MFIs in Ecuador. Our study shows the weight of the Social Performance dimension on the rankings compared with other dimensions. The practical significance of these results lies in that now it is possible to present a more comprehensive picture of the performance of MFIs. Besides, the methodology chosen can shed some light on the mission drift debate.

Keywords

Multicriteria Methodology; Social Performance; Ecuador; Microfinance institutions (MFIs); Mission drift

1. Introduction

In recent years it has been shown that people from the less privileged social strata may well have promising and feasible investment ideas that could materialize as profitable and successful businesses (Hollis and Sweetman, 1998).

However, inadequate access to credit by the less privileged has been identified as one of the main contributing factors to poverty (Akpalu et al. 2012). This has given rise to the so-called "microcredit" phenomenon, consisting of granting small loans to poor workers to enable them to develop their projects independently. These small loans are granted by a new type of financial organization, in many cases Non-Governmental Organizations (NGOs), known as Microfinance Institutions (MFIs). These organizations are in close contact with the local community and so can easily obtain information on those who apply for a loan. Da Silva (2007) states that before the creation of MFIs, bank loans were unavailable for poor people, and money lenders exploited many of the underbanked, especially in developing countries. In fact, although microfinance is often thought of as a tool to address poverty in developing countries, it is also being introduced in a number of countries in the developed world in order to address vulnerable groups (Barinaga, 2014). Thus, from the developing countries to the developed ones, microfinance is promoted as a key intervention for improving the lives of socio-economically vulnerable individuals (Rogaly, 1996).

Furthermore, these institutions are not solely dedicated to making a profit but are also interested in other aspects, such as developing local industries in rural and urban areas, creating jobs, promoting sexual equality, incorporating women into the labour market and in caring for the environment. Currently, microfinance facilitates financial inclusion and linkage (Ashta, 2009) and expands financing channels for vulnerable groups such as the less privileged.

Jonker (2009) defines microfinance as an economic innovation that has the goal to fight poverty. The most innovative aspect of the microfinance institutions is their *peer group loan methodolog*y, by which members jointly accept liability for the loans granted to the individuals in the group. This joint responsibility approach helps to keep default levels low, along with other aspects, such as: dynamic incentives, regular payments plans and collateral substitutes (Morduch, 1999). Another advantage of the system is that it strengthens the labour market and encourages enterprise in developing countries, especially among women in rural areas (Weber and Ahmad, 2014).

However, even though these organizations operate in a different way to traditional banks, it does not mean that they are not interested in other aspects, such as profits and/or efficiency. In fact, as Morduch (1999) has pointed out, when microcredit operations are analyzed very little consideration is given to the financial aspects and most of the attention is put on their sustainability and outreach (Yaron, 1994).

On the other hand, we can also differentiate between more profit-oriented MFIs (banks, non-bank financial institutions and cooperatives) and less profit-oriented MFIs, often constituted by NGOs. Barry and Tacneng (2014) found that NGOs socially perform better than other MFI organizational forms and that they are best conduits of Microfinance. Some literature (Hermes et al. 2011; Hoque et al. 2011) suggests that poverty alleviation practitioners are starting to grapple with the rise (both structurally and ideologically) of increased commercial banking in Microfinance. In other words, the very same commercial financial institutions that had earlier avoided poverty lending are starting to push and displace the microfinance field's foundational poverty alleviation and development principles over time.

In this line of thought, the evolution and expansion of MFIs have given rise to a series of informative indicators, many of which are standardized. Thus, in 2003, a consensus group formed by microfinance rating agencies, donors, multilateral banks and private voluntary organizations reached an agreement on the standards to be used in defining financial terminology, ratios, and their adaptation to microfinancing. The criteria were divided into four categories: sustainability/profitability, management of assets/debts, portfolio quality and efficiency/productivity (CGAP, 2003). Since then, numerous studies have been published on the first three aspects (Ahlin et al. 2011), although not a lot has been published on the efficiency/productivity of these institutions (Cervelló et al. 2015; Gutiérrez-Nieto et al. 2007; Wijesiri et al., 2015).

However, there is not a great deal of consensus as regards MFI social outreach indicators; on the contrary, different proposals have been made in the literature for measuring their performance in achieving their social objectives. The most commonly used is average loan size; some authors support the thesis that increased loan size means that the MFI abandon their poorer clients, or that they only stay with them if they are successful in business, in which case they are now not so poor (Mersland and Strom, 2010), thus weakening the social role of the MFIs. Hence, smaller loan sizes imply the greater social commitment of these institutions. The number of loans granted to women or to rural clients has also been used to measure the MFIs' social role. In fact, development communities have placed great emphasis on microfinance hoping that it may reduce poverty and advance women's empowerment in rural areas (Weber and Ahmad, 2014). As Islam et al. (2015) state an increasing proportion of the rural poor in many developing countries receive credit from microfinance institutions (MFIs). Hartaska et al. (2013) estimated that microfinance served more than 150 million borrowers. Most MFIs, especially the donor driven ones, usually target female borrowers who are believed to give high priority to basic needs such as health services, education, water and infrastructure and, therefore, are seen as important agents in the fight against poverty, especially in rural areas.

Some of these studies emphasize the fact that women find it harder to escape from poverty than men, so that microfinancing is seen as playing a crucial role in their emancipation. Also, women contribute to relieving poverty by giving priority to maintaining and improving the family's standard of living. Thus, increasing the women's access to microfinance could be a major contributing factor to increasing efficiency in output. For these reasons, generic indicators are included in the social objectives.

Some authors point to other aspects of microfinancing in rural areas (González-Vega, 2003; Christen and Rosenberg, 2006), while others deal with the particular cases of individual institutions or countries (Derflinger et al. 2006). Other works describe the application of certain specific risk-management tools, such as Barnett and Mahul (2007) or Skees and Barnett (2006). In general, the literature makes clear that the outreach of microfinance institutions is less advanced in the world of small agricultural firms in rural areas than in urban areas. Some of the diverse reasons given for this situation include: geographical location or the characteristics of agricultural production, the additional costs involved in operating in rural areas, the smaller number of financial products adapted to the needs of agricultural firms, or the concentration of risks due to the special production systems of these firms (González-Vega, 2003). For all these reasons, there is still an unsatisfied demand for investment funds from small agricultural producers or firms in rural areas. Recent estimates (Dalberg, 2012) indicate that both state and MFI loans jointly cover less than 2% of the potential demand for finance from these small producers. This means that microfinancing in rural areas still represents a challenge for MFIs, as their operations in these areas cannot be guaranteed to bring in profits.

Specifically, the trade-off between social goals and making a profit alludes to the concept of *mission drift*, which has emerged in recent years after the studies published by Copestake (2007) and Jones (2007), who considered the dilemma between profits and the social objectives which were initially considered to be the *raison-d'etre* of these organizations. In particular, Copestake (2007) suggested that greater integration with mainstream banking could imply greater emphasis on profits, efficiency and portfolio quality, at the expense of development and social goals, and from this viewpoint constructs a comprehensive amplified model to define the concept of mission drift.

In relation to this debate, a number of studies have attempted to empirically verify the existence of mission drift, e.g. Copestake (2007), Mersland and Strom (2010), Hermes et al. (2011), who, although they did find some cases of the phenomenon, also found that it was not widespread.

Some authors believe that financial and social objectives should be able to exist together; Gutiérrez-Nieto et al. (2007) propose a Data Envelopment Analysis (DEA) model to measure the financial and social efficiency of MFIs. In this vein, the purpose of this paper is to introduce an alternative methodology that allows considering social and financial goals when assessing the MFIs' performance. The methodological approach consists of a multiple criteria programming model and optimization method in which the solutions reduce the degree of non-compliance of possibly conflicting objectives.

Section 2 describes the method in depth, emphasizing its utility, and specifies the data sources used to arrive at a global performance assessment. Section 3 examines the results obtained by applying the method to a sample of MFIs operating in Ecuador in South America. The final section contains the main conclusions obtained in the study.

2. Methodology

2.1 The Goal Programming model

As mentioned above, a series of generally accepted indicators has been defined to allow comparable information to be obtained on different MFIs. They can also be used to order these institutions and there are numerous rankings that order MFIs in a given region according to total assets, volume of business, number of employees, etc. This approach to ordering by a single criterion or variable has a serious drawback, as focusing on a single variable provides no information on the other variables or on the overall position of a given entity within a reference group or comparison sector.

This paper therefore proposes to use a multicriteria ranking in an attempt to synthesize in a single index all the information obtained from different single-criterion rankings. As a novelty, we will also include in the multicriteria models the social and rural development aspects, together with the classic financial criteria mentioned above. This is done to obtain the trade-off between the social and financial objectives that has given rise to the mission-drift concept.

Various studies exist which use mathematical programming to study sustainability and development aspects in rural areas (Brandon et al. 2005). One of these proposed methods is known as CRITIC *(Criteria Importance Through Intercriteria Correlation)* (Diakoulakis et al. 1995). In this case, the importance of the criteria is considered in proportion to the singularity of the information they provide, so that the less a criterion overlaps with another, the higher its weighting will be. Another option is to use a modified version of TOPSIS *(Technique for Order Preference by Similarity to Ideal Solution)* (Deng et al. 2006) using Euclidean distances together with a measure of entropy to determine weights. Finally, another alternative is to use the well known *goal programming* technique (Charnes et al. 1955). A review of recent literature that uses this technique and includes socially responsible elements can be found in Ballestero et al. (2015). In the present work we propose the use of the goal programming technique presented by García et al. (2010a, 2010b) and García-Martínez et al. (2017) to obtain global performance.

Goal programming (Charnes et al., 1955) is a well known multicriteria technique consisting of both linear and non-linear functions and continuous or discrete variables in which all the functions have been transformed into objectives or goals (Ignizio and Romero, 2003; Prišenk et al. 2014). Unlike the optimization concept imposed by the mathematical models with a single objective function, goal programming can be interpreted under the philosophy of satisfaction, in the sense that from this point of view the decision-maker wants to minimize the non-achievement of his goals (Romero, 2001), since the simultaneous satisfaction of all the goals is rarely feasible.

The present study proposes combining the different rankings by means of different goal programming models (García *et al*. 2010a, 2010b; García-Martínez et al. 2017). According to the standard used, the solution obtained can be interpreted either as a solution in which there is maximum consensus between the measurements (penalizing the most conflictive as against those that follow the general trend), or as a solution in which the most conflicting measurements are given higher preference (penalizing those that share most information with the rest). In the first case, the absolute difference between the multicriteria value and the standardized value of the single criterion (norm L_1) is minimal. In the second, the greater difference between the multicriteria value and the standardized single-criterion value (norm L_∞) is minimal.

The norm L_1 goal programming model appears in (1):

$$Min \sum_{i=1}^{n}\sum_{j=1}^{c}\left(n_{ij}+p_{ij}\right)$$

$$s.t.$$

$$\textstyle\sum_{k=1}^{c}(w_k v_{ik})+n_{ij}-p_{ij}=v_{ij} \qquad i=1\ldots n \;\; j=1\ldots c$$

$$\textstyle\sum_{j=1}^{c} w_j = 1$$

$$\sum_{j=1}^{c}\left(w_j v_{ij}\right) = V_i \qquad i = 1 \dots n$$

$$\sum_{i=1}^{n}\left(n_{ij} + p_{ij}\right) = D_j \qquad j = 1 \dots c$$

$$\sum_{j=1}^{c} D_j = Z \tag{1}$$

where:

w_j = weight to be estimated for the j^th criterion.

$n_{ij}\left(p_{ij}\right)$ = negative (positive) deviation variable that quantifies the difference by excess (defect) between the value of the i^th MFI in the j^th criterion and the multicriteria value obtained by applying the weights w_j. Which is: $n_{ij} - p_{ij} = v_{ij} - \sum_{k=1}^{c}(w_k v_{ik})$, con $n_{ij}, p_{ij} \geq 0$.

The objective function of (1) ensures that only one of the deviation variables can have a value greater than zero: $n_{ij} \times p_{ij} = 0$.

D_j = degree of disagreement between the j^th criterion and the multicriteria value.

Z = magnitude of overall disagreement.

The model (1) has a total of $n \times c$ goal constraints. This means that for each criterion *j* (*j*=1…c) the model implements *n* constraints, one for each alternative *i* (*i*=1…n) and must determine the weight associated with criterion *j*, w_j. This is done by minimizing the difference in absolute terms between the performance of the single criterion of each alternative in criterion *j*, v_{ij}, and the multicriteria performance V_i, with $V_i = \sum_{j=1}^{c}\left(w_j v_{ij}\right)$. This value is the ultimate goal of the method, since on assigning a single value to each alternative as the total of all the single-criterion performances, the ranking of the alternatives is obtained immediately.

The value of the objective function provides the degree of non-achievement of the set of goals. The sum of all the weights is restricted to 1. The last constraints are used to compute the multicriteria performance of the MFIs (V_i), the degree of disagreement of each single-criterion measure with respect to the multicriteria value (D_j) and the degree of overall disagreement (Z). In the literature, the model that minimizes the sum of the absolute deviations is known as the *weighted goal programming* model (WGP) (Ballestero and García-Bernabeu, 2012; Romero, 2014).

The L_∞ norm is implemented by the MINMAX (2) goal programming model, in which D represents the maximum deviation between the multicriteria value and the single-criterion values. The remaining variables have the same meanings as in (1).

$$Min\ D$$

$$s.t.$$

$$\sum_{k=1}^{c}(w_k v_{ik}) + n_{ij} - p_{ij} = v_{ij} \qquad i = 1 \dots n \quad j = 1 \dots c$$

$$\sum_{i=1}^{n}(n_{ij} + p_{ij}) \leq D \qquad j = 1 \dots c$$

$$\sum_{j=1}^{c} w_j = 1$$

$$\sum_{j=1}^{c}(w_j c) = V_i \qquad i = 1 \dots n$$

$$\sum_{i=1}^{n}(n_{ij} + p_{ij}) = D_j \qquad j = 1 \dots c$$

$$\sum_{j=1}^{c} D_j = Z \tag{2}$$

The performance of alternative *i* in criterion *j* (v_{ij}) is normalized from the original variable (u_{ij}), so that $v_{ij} = (u_{ij} - u_{*j})/(u_j^* - u_{*j})$, with $u_j^* = \max_i u_{ij}$ and $u_{*j} = \min_i u_{ij}$. Normalization is necessary when the original variables are given in different magnitudes (e.g. monetary units, numbers of people, percentages, etc.). The solutions provided by models (1) and (2) represent extreme cases: favouring global consensus (WGP) or favouring the criterion that generates rankings with a high degree of idiosyncracy (MINIMAX GP).

As a compromise between (1) and (2) is the Extended Goal Programming model (3) in which the parameter λ provides more balanced solutions (González-Pachón and Romero, 1999; Linares and Romero, 2002). This extends the range of possibilities when deciding which multicriteria value is the most appropriate and representative of the individual criteria. It should be emphasized that if $\lambda = 1$ the same solution is obtained as in model (1), while if $\lambda = 0$ the solution coincides with model (2).

$$Min\, \lambda \sum_{i=1}^{n} \sum_{j=1}^{c} (n_{ij} + p_{ij}) + (1 - \lambda) D$$

$s.t.$

$$\sum_{k=1}^{c} (w_k v_{ik}) + n_{ij} - p_{ij} = v_{ij} \qquad i = 1 \dots n \quad j = 1 \dots c$$

$$\sum_{i=1}^{n} (n_{ij} + p_{ij}) \le D \qquad j = 1 \dots c$$

$$\sum_{j=1}^{c} w_j = 1$$

$$\sum_{j=1}^{c} (w_j v_{ij}) = V_i \qquad i = 1 \dots n$$

$$\sum_{i=1}^{n} (n_{ij} + p_{ij}) = D_j \qquad j = 1 \dots c$$

$$\sum_{j=1}^{c} D_j = Z \tag{3}$$

2.2 Other methodologies for ranking alternatives

In this section, we compare the proposed goal programming model with other well-known multicriteria methodologies which are used in the ranking of alternatives.

In fact, many of these methodologies were not initially proposed for the ranking of alternatives. In some cases, their original purpose was to determine the weights of criteria; however, this indirectly entails the performance of a ranking of alternatives.

Among the proposed methodologies which allow estimating the relative weights of the criteria, we can differentiate between objective methods and subjective methods. As Wierzbicki (2010) points out, the classical approach in multicriteria decision focuses on subjective rankings. This statement is based on the fact that human decisions are based on personal experience, memory, thoughts, thinking paradigms and the psychological states.

Among the methods that allow to organize the criteria in a hierarchy based on the decision maker's judgment and to infer a ranking of the alternatives, the Analytic Hierarchy Process (Saaty, 1980) is one of the most spread subjective methods[1].

Opposite to the approach of subjective methods, some management decisions are made individually by decision makers and affect many people. In these cases the decision maker wants to have a computerized decision support and rational ranking, and does not want to use personal preferences and subjective judgments. That is to say, he prefers to make decisions under the premise that his action will be justified to others by the use of an objective tool; thus, no one can doubt their honesty and impartiality. Wierzbicki (2010) puts as an example the companies that contract with third companies to asses them on issues that can be crucial for their development.

For example, when a CEO prioritize several investment options he might make a decision based on his own intuition. However, he could prefer to have the external and independent advice of another consulting firm, which would allow him to justify its decision when reporting the management committee, his partners and shareholders.

Full objectivity is not attainable, but in many situations we try to be as much objective as possible. As pointed out by some researchers, a deficiency of the subjective methods is that the weights of criteria may change depending on who the decision maker is. Therefore, different decision makers can assign different weights to the criteria and, as a consequence, the ranking of the alternatives can be seriously affected. The objective methods try to overcome this drawback.

Among the objective methods for the ranking of alternatives we can highlight the CRITIC method (Diakoulaki et al., 1995), TOPSIS (Deng et al., 2000), and even DEA through super efficiency (Charnes et al., 1978), despite the aim of DEA is not to rank the companies.

CRITIC is based on the idea that information contained in multicriteria decision-making problems is related to both contrast intensity and conflict of the decision criteria. According to Diakoulaki et al. (2000) a multicriteria problem in which the alternatives in all evaluation criteria are in

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[1] Regarding subjectivity, we refer to the explicit consideration of the judgments made by the decision maker and not to the mathematical procedure that is used to compute the relative weight of the criteria according to these judgments.

complete concordance, does not present any interest because the choice is evident. The introduction of a new criterion providing a different ranking of the alternatives adds new information and alters the decision situation. In addition, the notion of conflict is of primary importance in firm comparisons, since many financial ratios are often highly correlated.

The importance of the j-th criteria, C_j, is obtained through equation (4), where the intensity of each criterion j is computed as its standard deviation σ_j. The conflict is measured by $\sum_{k=1}^{c}(1-r_{jk})$, where r_{jk} is the correlation coefficient between j and k criteria.

$$C_j = \sigma_j \sum_{k=1}^{c}(1-r_{jk}) \tag{4}$$

Deng et al. (2000) propose a modified version of TOPSIS using weighted Euclidean distances combined with an entropy measure for calculating the weights. The amount of decision information emitted from each criterion is measured by e_j:

$$e_j = -k\sum_{i=1}^{n}(v_{ij} ln v_{ij}) \tag{5}$$

where $k = 1/ln(n)$ and the weight of each criterion is calculated proportionally to (6):

$$d_j = 1 - e_j \tag{6}$$

Therefore, in both cases it is considered that the greater the variability of the criterion, the greater the weight this criterion will have in the ranking. However, the modified version of TOPSIS does not take into account that some criteria may be partially or fully redundant, since they might be highly correlated and form part of the same dimension.

CRITIC and the model proposed in our work take into account this circumstance. However, as shown by García et al. (2010a) the solutions obtained by goal programming dominate those generated by CRITIC in the space considered by the authors. The goal programming model could obtain the optimal Pareto frontier of solutions, where other multicriteria models obtain a single solution. However, goal programming does not guarantee a Pareto optimal solution. In fact, goal programming was not designed with the purpose of obtaining non-dominated solutions but was developed as a method for finding satisficing solutions (Romero, 2014). If the intention of the decision maker is to achieve at least the goals' target values, then an optimal solution can be a non-efficient solution. For example, if a goal of the MFI is to reach at least 1,000 active borrowers, an optimal solution could simply satisfy this goal in a strict way. But an alternative optimal solution could achieve 1,200 active borrowers. Both solutions can be optimal, but the first one is non-efficient. In the case of model (3) both negative and positive deviations along with the maximum deviation are minimized in the objective function. This model is not intended to assure a minimum value in any specific goal; on the contrary, the multicriteria performance is designed to better approximate the single-criterion values.

With all this, a common drawback of these methods is that the linear aggregation of preferences expressed by the weighted sum tends to promote decisions with unbalanced criteria, as illustrated by the Korhonen paradox. In order to accommodate the natural human preference for balanced solutions, a nonlinear aggregation is necessary (Wierzbicki, 2010).

In addition to the multi-criteria approach, some authors point out some measures of concentration to adequately capture the dispersion of some variables (Lozza et al., 2013). Among the measures considered may be the Lorenz curve or the Gini index.

The Lorenz curve has been applied on economics as a graphical representation of the distribution of wealth (or income), and shows the proportion of wealth assumed by a percentage of the population. An equal wealth distribution where every person has the same wealth would be represented as a straight line. An unequal distribution would exhibit a curve.

The Gini coefficient also measures inequalities in a frequency distribution. A value of zero means perfect equality, where all wealth values are the same. A value of one means maximal inequality among the wealth values of the population.

So both Lorenz curve and Gini coefficient could be used to measure the dispersion of the wealth. In our problem, they could be used to measure how similar or dissimilar are the criteria. In this sense, we could think about these approaches in the same way on how partial correlations are used to measure the degree of association between two criteria, when the effect of other criteria has been removed.

2.3 Data

As already mentioned, the variables used in the works cited in the preceding section were considered when selecting the variables for this study. Special attention was paid to mean loan size, the variables linked to the rural environment and those that encouraged women to enter the labour market, together with others linked to financial performance, outreach and the characteristics of the MFIs themselves. The following performance dimensions and their most representative variables were thus considered: Institutional Characteristics (IC), Outreach (OU), Overall Financial Performance (OFP) and Social Performance (SP). As is normal in studies on performance, certain areas were assigned different variables referring to different aspects. Table 1 shows these variables together with the global performance dimensions, or the categories in which they are found and therefore represent.

All the criteria are directly combined in the global performance ranking, assuming that the greater the value of one of the criteria, the greater the perception of performance, with the exception of the average loan balance per borrower (ALBPB), in which, in view of the above-cited definition of mission drift, it was considered that the lower the value the higher the performance ("the less is better"), since it allowed a higher number of borrowers to be included and thus gave a larger population easier access to finance, especially among the less privileged. The data base used in the study was obtained from data collected from MIX Market reports, published by Microfinance Information Exchange (2012), a global web-based microfinance information platform and the main source of social and financial performance data relating to MFIs.

Information was collected for the 33 MFIs operating in Ecuador with data available at the MIX Market reports, in relation to the above-mentioned variables for the year 2012.

3. Results

3.1 Global Performance

The original variables having been normalized, the variables shown in Table 1 are used as the starting point. On solving (3) for different values of $\lambda \in [0,1]$, we first obtain the weighting or relative importance of the individual criteria in the global performance ranking, and secondly the multicriteria value that places the MFI in the ranking according to global performance.

[Table 1 here]

Table 2 shows the results obtained according to the values assigned to the λ parameter. For each of these values, we give the weights of each criterion, the deviation between multicriteria performance and each of the D_j (j = 1…12) criteria, maximum deviation D between criteria, and global deviation Z as the sum of all the D_j .

[Table 2 here]

For λ=1 the model obtains non-null coefficients for all variables except A, P and %GRLP. The first two belong to the Institutional Characteristics dimension, which means they do not contribute to global activity/performance. However, the A variable does begin to have a certain influence on λ values between 0.6 and 0.1, both inclusive. It should be emphasized that NAB, ALBPB and GLP have a considerable influence, followed by %NARB, although the latter loses its influence after λ = 0.5, giving way to the other rural development indicator %GRLP. It can therefore be concluded that the Outreach and Social Performance dimensions are the best representatives of the general tendency of global activity/performance. In fact, when the weights of all the variables that represent these two dimensions (80.45% for OU and 18.92% for SP) are added together, a value of 99.37% is obtained, and the remaining 0.63% is explained by the only measure of Overall Financial Performance, the Return on Equity (ROE) variable.

It can be seen that as the value of λ drops, the number of variables involved in calculating global activity/performance stays the same, except for λ=0.9, λ=0.3 and λ=0.2, in which the number is reduced to five. For the λ=0 extreme, only three variables have non-null coefficients: GLP (that belongs to OU), %GRLP and %FB (that belong to Social Performance). This confirms that these three are very different from the rest as regards the information they provide on global performance. In fact, neither Overall Financial Performance nor the variables linked to active borrowers have any influence whatsoever, in spite of being decisive in the $\lambda = 1$ model.

Also, it can be seen that for the D_j values of the variables, in almost all cases D_6 and D_7 *have* the highest values, followed by D_9 for the different values of λ and, in most cases, coincide with the highest deviation D. This means that %NARB and %GRLP are the variables most in disagreement with the other single-criteria that measure global performance, followed by %FB. In other words, the percentage of total active borrowers in rural areas, the percentage of the global portfolio assigned to these areas, and the percentage of women borrowers are the variables that agree least with the consensus of the other variables. This is of great interest, since all three variables are included in the Social Performance dimension and therefore confirm the existence of an incentive to mission drift by the MFIs, so that, on being concentrated in these social goals, the other variables give a reduced perception of performance.

The bottom rows in Table 2 give the weights of each of the dimensions in the analysis, obtained as the sum of the weights of each criterion. It can be clearly seen that as the value of λ is reduced, the Outreach and Overall Financial Performance dimensions concede part of their weight to Social Performance and occasionally to Institutional Characteristics. It can thus be seen that for the smallest λ values the influence of the weight of the Social Performance dimension is higher than 50%.

In spite of the fact that the weight of each criterion, or of the set of criteria calculated for the dimension, offers an idea of the relative importance of each measure in calculating global performance, with the aim of verifying the existence of mission drift in the global performance of the MFIs we carried out a Spearman's correlation analysis in order to study the correlation between the individual measures of each criterion and the global performance of the MFIs included in the study. These correlation levels are given in Table 3. It can be seen that the variables with the highest degree of correlation are %GRLP, with values between 0.208 (λ= 0.5) and 0.808 (λ= 0.3) and %NARB, with values between 0.196 (λ= 0.5) and 0.763 (λ= 0.3). Overall, it can be stated that on favouring the maximum consensus between the measures (penalizing the most conflictive measures in comparison with those that follow the general tendency) it can be seen that the highest correlations are for Outreach and Institutional Characteristics, although some social variables also show a certain positive correlation. On the other hand, on searching for a solution in which the most conflictive measures are given greater preference (lower λvalues) the rural variables show the highest correlation. Then, we could say that in general terms there is no conflict between global performance and social indicators, letting little room to the appearance of mission drift. Besides, it should be pointed out that both ROE and ALBPB hardly show one significant correlation throughout the entire range of the analysis, which raises questions on their validity as measures of global performance.

[Table 3 here]

3.2 Ranking of Ecuadorian microfinance institutes

Bearing in mind the need to not only analyze the ranking on the basis of final performance, but also on the decisive role of this type of result on decision-making processes, the different MFI rankings obtained by the model were also analysed.

Of the Ecuadorian MFIs analyzed, those that obtained the best positions were: *Banco Solidario, COAC Jardín Azuayo* and *Fundación Espoir,* in the first quartile for all values of λ; those with the lowest positions in the ranking were: *COAC Artesanos, COAC Chone, COAC Luz del Valle* and *FUNDAMIC,* which were always positioned in the last and/or third quartile.

As regards dispersion, four MFIs were always found together in the same quartile: *Banco Solidario, COAC Jardín Azuayo* and *Fundación Espoir* (first quartile) and *COAC Kullki Wasi* (second quartile). It is also interesting to note that only one, *FINCA-ECU,* occupied positions in all the quartiles, and that in more than 50% of the results the 33 MFIs occupied the same position, which indicates the robustness of the results (see Table 4).

[Table 4 here]

4. Conclusions

The performance of MFIs has traditionally been measured by means of ratios. However, this approach cannot detect any possible conflict between social and financial goals, also known as the mission drift concept. Unlike activity and performance rankings based on a single criterion, the goal programming multicriteria method proposed in this paper provides an estimate of the performance of an MFI, by simultaneously combining individual criteria linked not only to financial and outreach dimensions, but also to the Social Performance dimension. In particular, literature considers within such dimension the economic development of rural areas, the incorporation of women into the labour market and the granting of small loans to the less privileged as part of the social goals. Hence, we add these indicators in the estimates. The proposed method was used to obtain the multicriteria ranking of a sample of MFIs at present operating in Ecuador.

The goal programming technique was used to calculate weights considering the existing similarities between the values of different criteria and global performance, the latter value being finally used to measure the performance of the MFIs. By applying different versions of the goal programming model, a collective approach was used (in which higher weights were given to criteria with similar results and lower weights to the more heterogeneous), as well as an individual approach (higher weights to the most heterogeneous). Moreover, as a compromise solution between both approaches, a parametric version was developed with the aim of widening the range of possibilities open to decision makers, in such a way that the previous approaches were converted into particular cases of the third approach.

The results for the sample show that, for every value of the weight parameter chosen, certain MFIs are always found in the first positions, while others are always placed in the last. From this we can conclude that there are two clear groups of Ecuadorian MFIs which perform better and worse than the average, regardless of the measure of performance chosen.

Therefore, the good or bad performance does not seem to be affected by the focus on social or financial goals by these MFIs and so the mission drift seems not to appear in the sample.

Nevertheless, the correlation analysis carried out confirms this finding on the mission drift, while simultaneously giving a slightly more nuanced picture on this respect. Rural lending indicators chosen are found to have a certain correlation with global performance at every parameter level, therefore the focus on rural lending seems to allow MFIs to achieve good results in the *usual* performance dimensions. To a lesser degree, the focus on the female borrowers follows the same direction. On the other hand, the most commonly used indicator of social performance -the average loan per borrower- neither follows nor goes in conflict with the *usual* performance dimensions.

Furthermore, the weight of the variables of the Social Performance dimension have a considerable influence on the rankings, as this weight increases as singular criteria are sought. In view of the results obtained, it can be concluded that an increase in the portfolio of loans granted to borrowers in rural areas, in the number of active borrowers in rural areas, and in the percentage of women borrowers would give a better global performance to each of the MFIs.

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Table

Table 1

Variables used

Variable	Dimension
Assets (A)	*Institutional Characteristics (IC)*
Personnel (P)	*Institutional Characteristics (IC)*
Number of Active Borrowers (NAB)	*Outreach (OU)*
Gross Loan Portfolio (GLP)	*Outreach (OU)*
Return on Equity (ROE)	*Overall Financial Performance (OFP)*
% Number of active rural borrowers (%NARB)	*Social Performance (SP)*
% Gross rural loan portfolio (%GRLP)	*Social Performance (SP)*
Average loan balance per borrower (ALBPB)*	*Social Performance (SP)*
% Number of Female Borrowers (%FB)	*Social Performance (SP)*

*In order to comply with “the less is better” the ALBPB variable was reversed.

Table 2
Numerical results according to value of parameter λ

Weights		A	P	NAB	GLP	ROE	%NARB	%GRLP	ALBPB	%FB
λ	1	0.0000	0.0000	0.5267	0.2778	0.0063	0.0885	0.0000	0.5080	0.0050
	0.9	0.0000	0.0000	0.4505	0.2967	0.0000	0.1409	0.0000	0.0599	0.0521
	0.8	0.0000	0.0000	0.4236	0.2830	0.0012	0.1463	0.0000	0.0953	0.0506
	0.7	0.0000	0.0000	0.4272	0.2765	0.0061	0.1459	0.0000	0.0988	0.0454
	0.6	0.0579	0.0000	0.4611	0.1372	0.0000	0.2092	0.0000	0.0852	0.0495
	0.5	0.0000	0.0000	0.5087	0.1024	0.0380	0.0960	0.2031	0.0517	0.0000
	0.4	0.0192	0.0000	0.4222	0.1011	0.0496	0.0000	0.3521	0.0558	0.0000
	0.3	0.1091	0.0000	0.3454	0.0000	0.0813	0.0000	0.3950	0.0693	0.000
	0.2	0.1091	0.0000	0.3454	0.0000	00813	0.0000	0.3950	0.0693	0.0000
	0.1	0.2802	0.0000	0.1879	0.0000	0.0141	0.0000	0.4153	0.0206	0.0819
	0	0.0000	0.0000	0.0000	0.4517	0.0000	0.0000	0.3976	0.0000	0.1507

Source: Authors' calculations

Table 2 (continuation)
Numerical results according to value of parameter λ

Distances		D	D1	D2	D3	D4	D5	D6	D7	D8	D9	Z
λ	1	13.3836	3.7073	2.9344	2.6123	3.8403	10.3602	13.3836	12.9061	5.7424	10.7796	66.2663
	0.9	12.5983	4.3732	3.6897	3.4044	4.5062	9.6090	12.5983	12.1229	5.8136	10.2505	66.3678
	0.8	12.3670	4.6843	3.9587	3.6110	4.8173	9.4150	12.3670	11.9075	5.6148	10.0300	66.4057
	0.7	12.3478	4.7006	3.9763	3.6206	4.8336	9.40239	12.3470	11.8927	5.6089	10.0340	66.4167
	0.6	11.4374	5.6432	4.8959	4.3058	5.7762	8.7706	11.4374	10.9890	5.6979	9.4717	66.9878
	0.5	10.3004	6.5518	5.9787	5.1809	6.6808	8.0039	10.3004	9.8355	6.2931	9.1975	68.0221
	0.4	9.4312	7.3701	6.8420	6.0567	7.4298	7.6477	9.4312	8.9751	6.5469	8.8791	69.1092
	0.3	8.4215	8.3061	7.8798	7.1132	8.4215	7.3173	8.4215	8.0210	6.9886	8.4215	70.8903
	0.2	8.4215	8.3061	7.8798	7.1132	8.4215	7.31731	8.4215	8.0210	6.9886	8.4215	70.8903
	0.1	8.3309	8.2284	7.8962	7.4342	8.33097	7.6641	8.3309	7.94415	7.2793	8.3309	71.4391
	0	8.2637	8.2637	7.9956	7.9144	82637	8.2637	8.2637	8.2637	7.6355	8.2637	73.1274

Source: Authors' calculations

Table 2 (continuation)
Numerical results according to value of parameter λ

Dimensions		IC	OU	OFP	SP
λ	1	0.0000	0.8045	0.0063	0.1892
	0.9	0.0000	0.7471	0.0000	0.2529
	0.8	0.0000	0.7066	0.0012	0.2922
	0.7	0.0000	0.7037	0.0061	0.2902
	0.6	0.0579	0.5983	0.0000	0.3438
	0.5	0.0000	0.6111	0.0380	0.3509
	0.4	0.0192	0.5233	0.0496	0.4079
	0.3	0.1091	0.3454	0.0813	0.4643
	0.2	0.1091	0.3454	0.0813	0.4643

0.1	0.2802	0.1879	0.0141	0.5178
0	0.0000	0.4517	0.0000	0.5483

Source: Authors' calculations

Table 3.

Spearman's correlation coefficient

λ		A	P	NAB	GLP	ROE	%NARB	%GRLP	ALBPB	%FB
	1	0.588	0.524	0.668	0.591	0.055	0.354	0.368	-0.002	0.124
	0.9	0.503	0.450	0.575	0.508	-0.009	0.424	0.444	0.023	0.184
	0.8	0.407	0.496	0.638	0.418	0.050	0.297	0.311	-0.060	0.076
	0.7	0.442	0.387	0.528	0.444	-0.026	0.445	0.459	0.088	0.182
	0.6	0.373	0.307	0.452	0.374	0.013	0.527	0.550	0.121	0.213
	0.5	-0.229	-0.245	-0.142	-0.203	0.078	0.196	0.208	0.186	-0.025
	0.4	0.203	0.114	0.266	0.201	0.140	0.728	0.771	0.176	0.311
	0.3	0.112	0014	0.178	0.109	0.224	0.763	0.808	0.199	0.327
	0.2	0.112	0.014	0.178	0.109	0.224	0.763	0.808	0.199	0.327
	0.1	0.164	0.047	0.188	0.162	0.107	0.738	0.778	0.123	0.342
	0	0.210	0.077	0.195	0.211	0.098	0.687	0.730	0.011	0.276

Source: Authors' calculations

Table 4

Position according to interquartile frequency

Name	1st quartile	2nd quartile	3rd quartile	4th quartile
Banco Solidario	11			
CACMU	5	6		
CCC	2	6	3	
CEPESIU		3	7	1
COAC 4 de Octubre		1	9	1
COAC Ambato	1	4	6	
COAC Artesanos			1	10
COAC Atuntaqui		4	7	
COAC Chone			1	10
COAC Fernando Daquilema		10	1	
COAC Jardín Azuayo	11			
COAC Kullki Wasi		11		
COAC La Benéfica		1	6	4
COAC Luz del Valle			1	10
COAC Padre Vicente	1	9	1	
COAC San Antonio		1	6	4
COAC San Gabriel			3	8
COAC San José	7	4		
COAC Santa Anita			3	8
CODESARROLLO		3	5	3
COOPROGRESO	6	3	2	
FACES			2	9
FINCA – ECU	4	1	5	1
FODEMI	7	4		
Fundación Alternativa		7	4	
Fundación Espoir	11			
FUNDAMIC			1	10
INSOTEC		6	5	
ProCredit - ECU	6	2	3	
UCADE Ambato	10	1		
UCADE Guaranda	10			
UCADE Latacunga	9	2		
UCADE Santo Domingo		4	7	

Source: Authors' calculations