Haute école de gestion de Genève
CRAG - Centre de Recherche Appliquée en Gestion
Cahier de recherche

Measuring the Performance of Microfinance Institutions

Giovanni FERRO LUZZI
Sylvain WEBER

Cahier : N° HES-SO/HEG-GE/C--06/3/1--CH

2006

Measuring the Performance of Microfinance Institutions[*]

Giovanni FERRO LUZZI[§]
Sylvain WEBER[‡]

Cahier de recherche

juillet 2006

[*] The authors wish to thank Yousra Hamed for assistance with the data used in this paper and Yves Flückiger for fruitful comments. The usual caveat applies.

[§] University of Geneva, giovanni.ferro-luzzi@ecopo.unige.ch

[‡] Geneva School of Business Administration (HEG Genève), University of Applied Sciences of Western Switzerland (HES SO), e-mail: sylvain.weber@hesge.ch.

Résumé

Mesurer la performance des institutions de microfinance (IMF) n'est pas une tâche aisée. Étudier la seule capacité financière d'une IMF est en effet insuffisant, puisque cela ne constitue qu'une facette de sa performance. De nombreuses IMF étant initialement créées dans l'objectif d'aider les plus pauvres, il est en fait nécessaire de tenir compte d'aspects sociaux. La performance des IMF est par conséquent multidimensionnelle.
Ce papier illustre une approche moderne pour évaluer la performance des IMF. L'analyse factorielle est utilisée dans un premier temps afin de construire des indices de performance basés sur de multiples combinaisons de variables potentielles. Les variables de base sont ainsi combinées pour produire plusieurs facteurs contenant chacun une dimension différente de performance. Les scores factoriels assignés à chaque IMF peuvent ensuite être utilisés comme variables dépendantes d'un modèle à équations simultanées. Cette méthodologie nous permet de présenter de nouveaux résultats concernant les facteurs déterminant la performance des IMF.

Mots-clés

Microfinance, Performance sociale, Performance financière, Analyse factorielle

Summary

Measuring the performance of microfinance institutions (MFIs) is not a trivial task. Indeed, looking at the financial sustainability of an MFI only gives one feature of its performance. As many MFIs primarily exist in order to help the poorest people, one also has to include aspects of outreach in their performance. Hence, MFIs' performance can be termed multidimensional.
This paper illustrates how some statistical tools can offer new insights in the context of MFIs' performance evaluation. Factor analysis is used in a first step to construct performance indices based on several possible associations of variables without posing too many a priori restrictions. The base variables are thus combined to produce different factors, each one representing a distinct dimension of performance. We then use the individual scores ascribed to each MFI on each factor as the dependent variables of a simultaneous-equations model and present new evidence on the determinants of MFIs' performance.

Keywords

Microfinance, Outreach, Self-sustainability, Factor analysis

1. Introduction

Microfinance has attracted much attention in the recent years. Some commentators have brimmed over with enthusiasm and optimism and see microfinance as the panacea to under-development. By resting on market incentives, microcredit is able to promote small scale investment that generates sufficient revenues from otherwise unrealized market activities while yielding a return on the amount lent. This is a powerful lever to provide credits and deposits possibilities to poor individuals who are largely ignored by commercial banks and other lending institutions. The reasons of this neglect are many. Often, such credits are just not profitable enough for banks, because of economies of scale. By focusing on small amounts, and easing collateral requirements, microfinance institutions (MFIs) are better equipped to target poor individuals or groups who need resources to finance small scale investments.

These credits can be sufficient to promote autonomous and profitable economic projects, expand the opportunity set faced by poor individuals and thereby alleviate poverty. Hence, MFIs, once set up and independent, should be able to generate “win-win” outcomes, whereby both efficiency and equity are enhanced. Very often, however, and depending on some exogenous factors, like infrastructure or access to markets, microcredit must be subsidized to ensure the survival of the MFIs.

Others have found the evidence to be not so favorable to this argument. Many MFIs seem to have trouble reaching self-sustainability at the financial level, even after the setup period. In this case, microcredit becomes more akin to subsidized credit which has a long record in developing countries, but has often failed to achieve lasting positive results (Morduch, 2000).

Still, even if MFIs do not reach financial sustainability and fail therefore to conform to the “win-win” assumption, they can still be considered valuable if they provide credit facilities to poor households who would not be able to find financial resources otherwise. In this perspective, *outreach* has a social value in itself, which may more than offset the cost associated with permanent financial subsidies needed by the MFIs.

In other words, MFIs face a double challenge: not only do they have to provide financial services to the poor (*outreach*), but they also have to cover their costs in order to avoid bankruptcy (*sustainability*). Both dimensions must therefore be taken into account in order to assess their performance.

There is currently no widely accepted measure for assessing the social performance of MFIs, outreach always being defined in terms of several indicators, like the percentages of female and rural clients or the average loan size (Schreiner, 2002). Very few attempts have been made to aggregate those numerous indicators into one single measure, although it would be useful since it would give a straight and accurate view of the outreach. Zeller *et al.* (2003) provide some hints for building such a measure, either by assigning arbitrary weights to each of the indicators, or by deriving the weights through principal components analysis. In this paper, we generalize their second method: we apply factor analysis[1] to a set of indicators not only related to social performance but also to financial performance. Each of the factors created will represent one dimension of performance, according to the indicators they are composed of.

The factors determining MFIs’ performance are not clearly known either. To the best of our knowledge, Hartarska (2005) was the first to present evidence on the determinants of MFIs’ performance in a multidimensional context. However, she estimates different equations for each of the indicators. The methodology we propose here goes two steps further. First, using factor analysis, we create a synthetic index for each of the two dimensions. We calculate thereafter how each MFI scores for each of these indices and use the values obtained as the dependent variables of a regression. In so doing, we need only estimate one equation for outreach and one for sustainability. Secondly, instead of estimating single equations, we will make use of a simultaneous-equations model, to take account of a possible dependence between outreach and sustainability. Even if the relationship between outreach and sustainability is still not clearly determined yet (Conning, 1999; Zeller & Meyer, 2002), one can assume there exist some links and must allow the equations to be connected.

The rest of the paper is organized as follows. The next section briefly describes the data set used for our empirical estimations. Section 3 presents the principles of factor analysis as well as the results obtained with this technique on our sample. In order to have a better understanding of the factor analysis results, we use cluster analysis to create groups of MFIs in section 4. The second step of the analysis is explained in section 5, where we look for the

[1] Like principal component analysis, factor analysis is a statistical method that attempts to explain a set of multivariate data using a smaller number of dimensions than one begins with.

determinants of MFIs' performance. The final section summarizes the main results and concludes.

2. The Data

The sample used is this paper is composed of 45 microfinance institutions surveyed by the *Graduate Institute of Development Studies* of Geneva for the period 1999-2003. Hamed (2006) provides a complete description of the data set, and we describe here only the variables selected for our analysis.

We retained six variables among the huge quantity that were collected to perform the factor analysis. We were in fact constrained by the relatively small number of MFIs surveyed. Indeed, factor analysis is data consuming and it would not have made any sense to include too many variables on such a small sample of observations. The six variables retained are described in Table 1.

The majority of these variables are indicators of outreach. The loan size is usually taken as a proxy for the *depth* of outreach, which can be defined as the value that society attaches to the net gain of a given client, following the terms of Schreiner. It is only when the average loan size is very small that the MFI touches the really poor. The percentage of female borrowers is a proxy for the depth of outreach as well, since loans to women are more highly valued by society. One can also expect that an MFI will serve poorer individuals if it lends to groups. Hence, the higher the share of borrowers organized in groups, the deeper the outreach. The use of poverty criteria indicates the MFI is more oriented toward poorer people, so that when *POVCRIT* equals 1, the outreach should be enhanced. As a lender who does not impose physical collateral to its clients could serve poorer users and thus reach deeper outreach (Navajas *et al.*, 2000), a deeper outreach will be attained if *COLLATERAL* is 0.

Actually, only the last variable *OSS* represents a financial measure. It would have been interesting and desirable to include other variables related to sustainability, like the Return On Assets (*ROA*) or the Return On Equity (*ROE*). Unfortunately, they had far too many missing values in our data set, which made them unusable for our present purposes.

Table 1: Description of variables

Variable	Description	Values
FEMALE##	Percentage of female borrowers	continuous variable (%)
GROUPLOAN##	Lending methodology: percentage of active clients organized in groups	continuous variable (%)
POVCRIT	Use of poverty criteria to target clients	0 = no 1 = yes
COLLATERAL	Assets required as collateral	0 = no 1 = yes
LOANSIZE##	Average loan / GNP per capita	continuous variable (%)
OSS##	Operational Self Sufficiency (Total revenues / Total expenses)	continuous variable

3. The multiple dimensions of MFIs' performance

3.1 Factor analysis from a theoretical point of view

The main idea to use factor analysis in the context of MFIs' performance is to exploit the fact that there are several components of performance (sustainability and outreach), each of which translates into many observable variables. From these many variables, factor analysis will enable us to create one synthetic indicator for each dimension considered: one for outreach and one for sustainability. Each dimension will be composed of a combination of the observed variables described in Table 1. With the data we have at hand, we expect *OSS* to capture the sustainability dimension in itself, since it is the only financial variable available. We also expect all other variables to be combined in another factor to create the outreach dimension of performance.

Formally, factor analysis assumes that each measured variable x_j is due to some unobserved common factors f_k and an idiosyncratic effect s_j:

$$x_j = \sum_k a_{jk} f_k + s_j$$

or, in matrix notation: $\mathbf{x} = \mathbf{A} \cdot \mathbf{f} + \mathbf{s}$,

where the **x** vector includes all observed (standardized) variables, **A** is the matrix of factor loadings, **f** is the vector of (latent) common factors, and **s** is similar to a residual, and includes what is known as the variables' unique factors.

One problem we must address is the fact that some of our variables are dichotomous. In such instances, it is known that the Pearson's correlation matrix is biased and will unavoidably lead to biased estimates of the factor loadings if used as the basis for a factor analysis (Olsson, 1979). We will thus need to calculate different types of correlation coefficients, according to the nature of each pair of variables:

- *tetrachoric* between two dichotomous variables
- *polyserial* between one dichotomous variable and one continuous variable
- *Pearson's* between two continuous variables.

The resulting matrix will then be used as the starting point of the factor analysis.

The first step in factor analysis is to decide how many factors are relevant to the model. As we shall see in the empirical part, this choice is guided by some simple rules.

The next problem encountered is that the factor loadings matrix **A** defined above is not uniquely determined. To ensure a solution, one has to introduce constraints on the parameters in the original model. In general, one requires the first factor to have maximal contribution to the common variance of the observed variables, the second to have maximal contribution to this variance subject to being uncorrelated with the first, and so on. However, it is possible that a more interpretable solution can be achieved using a transformed model, obtained by a process known as *factor rotation*. Various methods for the rotation of factors are available and we will make use of an oblique one (*promax* with power 3), which allows the factors to be correlated, rather than independent. In our case, this is indeed what we want, as we expect the different dimensions of performance to be linked: MFIs can be performant on both dimensions at the same time, even if it is likely that MFIs trying to be the most socially performant will encounter some difficulty to be financially effective. Trade-offs are sometimes inevitable, but synergies among the different dimensions are also possible (Zeller & Meyer, 2002).

Once a representation of the data in this form is considered adequate, every MFI can be ascribed a *score* on each derived factor that will inform us on how it behaves on the corresponding dimension of performance.

3.2 Factor analysis: Empirical results

Now that factor analysis has been shortly exposed from a theoretical point of view, we turn to the empirical results. Even if the same analysis has been made for each available year (1999-2003), some figures (comparable across years) will only be displayed for 2003 for the sake of space.

As stated before, the correlation matrix is the departure point of the factor analysis. It is therefore interesting to have a look on correlations, which are shown here for 2003.

Table 2 immediately confirms that the first five variables pertain to a similar group, since their correlation is quite high in absolute value. On the contrary, the correlation between the operational self sufficiency and the other variables is very weak. We therefore expect that the

Table 2: Correlation matrix for 2003

	FEMALE03	***GROUPLOAN03***	***POVCRIT***	***COLLATERAL***	***LOANSIZE03***	***OSS03***
FEMALE03	1.000					
GROUPLOAN03	0.417	1.000				
POVCRIT	0.554	0.504	1.000			
COLLATERAL	-0.600	-0.631	-0.885	1.000		
LOANSIZE03	-0.450	-0.314	-0.792	0.810	1.000	
OSS03	0.263	0.017	0.098	-0.115	0.042	1.000

latter will constitute a dimension by itself in the factor analysis. This matrix of correlations is then used to extract the factors via principal component factors.

The next step involves choosing the appropriate number of latent factors. To this end, we rely on some standard statistical and visual tools, commonly used in factor analysis, although one should be aware that most of these rules are somehow *ad hoc* and cannot avoid value judgments. One method which has been put forth is to exclude factors with eigenvalues smaller than one, since the factors retained in this way account for more variance than the average for the variables. Another method is to keep just enough factors so that the cumulated variance explained is no less than 70%. Eventually, an examination of the plot of the eigenvalues against the corresponding factor numbers, the so-called *Scree Diagram* (see Figure 1), can help the choice. The rate of decline tends to be fast for the first few factors but then levels off. The "elbow", or the point at which the curve bends, is considered to indicate the maximum number of factors to extract. Another way to use the Scree plot is to draw a straight line connecting the lowest eigenvalues, the threshold being where this line separates from the eigenvalues' line.

Table 3 contains the eigenvalues, as well as the associated proportion of variance explained by each latent factor for years 1999-2003. Based on this information, it is quite easy to choose two factors. Indeed, all of the criteria given above indicate that the two-factor solution is the best for every year. First of all, we get two eigenvalues higher than one for every year. Secondly, if we want to keep enough factors to have a cumulated variance of 70%, we should keep two factors. Finally, as can be seen from Figure 1 (only drawn for 2003), the third and following eigenvalues are located on a straight line, indicating a two-factor solution as well.

Next, we apply a rotation of the factors to provide a more meaningful and easily interpretable solution loading matrix. As previously stated, it makes sense to allow the different dimensions of performance to be correlated. We therefore apply an oblique rotation that involves the introduction of correlations between factors. The resulting loadings are presented in Table 4. Once again, very similar results are found for each year.

Figure 1: Scree plot for 2003

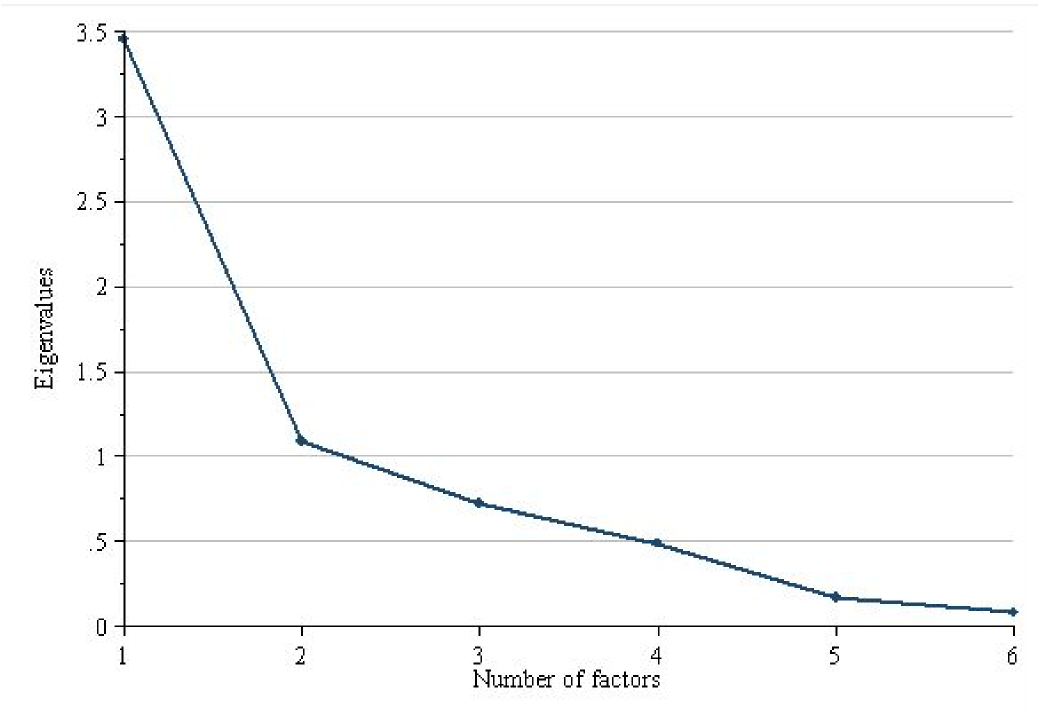


Table 3: Eigenvalues and proportion of variance explained

Year	Factor	Eigenvalue	Proportion	Cumulative
1999	1	3.274	0.546	0.546
	2	1.050	0.175	0.721
	3	0.684	0.114	0.835
	4	0.599	0.100	0.934
	5	0.286	0.048	0.982
	6	0.106	0.018	1.000
2000	1	3.286	0.548	0.548
	2	1.044	0.174	0.722
	3	0.864	0.144	0.866
	4	0.655	0.109	0.975
	5	0.138	0.023	0.998
	6	0.012	0.002	1.000
2001	1	3.366	0.561	0.561
	2	1.081	0.180	0.741
	3	0.604	0.101	0.842
	4	0.537	0.090	0.931
	5	0.313	0.052	0.984
	6	0.099	0.017	1.000
2002	1	3.523	0.587	0.587
	2	1.017	0.170	0.757
	3	0.712	0.119	0.875
	4	0.503	0.084	0.959
	5	0.167	0.028	0.987
	6	0.076	0.013	1.000
2003	1	3.454	0.576	0.576
	2	1.087	0.181	0.757
	3	0.724	0.121	0.878
	4	0.486	0.081	0.959
	5	0.167	0.028	0.987
	6	0.081	0.014	1.000

A glance at Table 4 reveals that *FEMALE*, *GROUPLOAN* and *POVCRIT* load positively and quite highly on the first factor, indicating that a higher value of these variables leads to a higher score on the factor 1. On the contrary, *COLLATERAL* and *LOANSIZE* load strongly and negatively, meaning that the MFI which has a smaller value for one of these two variables will have a higher score on factor 1, everything else equal. Since a deeper outreach is associated with a higher value of *FEMALE*, *GROUPLOAN* and *POVCRIT* and a smaller value of *COLLATERAL* and *LOANSIZE*, factor 1 clearly reflects the social dimension of performance and can be termed “social performance”. The second factor is clearly related to financial efficiency, since *OSS* is the only variable that exhibits a loading of considerable size. We therefore label this factor “financial performance”.

As shown in Table 5, the correlation between the two factors is low and its sign is not consistent across the five years. Consequently, our results do not confirm nor contradict the existence of a trade-off between the two dimensions of performance.

Table 4: Rotated factor loadings (oblique rotation) and unique variances

Year	Variable	Factor 1	Factor 2	Uniqueness
1999	*FEMALE99*	0.7060	0.1508	0.4861
	GROUPLOAN99	0.6583	0.1616	0.5479
	POVCRIT	0.9092	0.0147	0.1740
	COLLATERAL	-0.8793	0.2766	0.1336
	LOANSIZE99	-0.8421	0.0308	0.2881
	OSS99	-0.0964	0.9686	0.0460
2000	*FEMALE00*	0.5788	0.2385	0.5898
	GROUPLOAN00	0.6339	0.0885	0.5829
	POVCRIT	0.9539	0.0735	0.0754
	COLLATERAL	-0.9465	0.0608	0.1080
	LOANSIZE00	-0.8627	0.2565	0.2194
	OSS00	-0.0862	0.9536	0.0941
2001	*FEMALE01*	0.7605	0.1180	0.4323
	GROUPLOAN01	0.6365	-0.2834	0.4652
	POVCRIT	0.9264	0.0837	0.1560
	COLLATERAL	-0.9475	-0.1249	0.1189
	LOANSIZE01	-0.7842	0.1586	0.3259
	OSS01	0.1006	0.9806	0.0553
2002	*FEMALE02*	0.5956	0.3862	0.3708
	GROUPLOAN02	0.6799	-0.0558	0.5553
	POVCRIT	0.9606	-0.0497	0.1009
	COLLATERAL	-0.9403	-0.0507	0.0872
	LOANSIZE02	-0.8779	0.1343	0.2754
	OSS02	-0.0716	0.9812	0.0704
2003	*FEMALE03*	0.6307	0.3899	0.3636
	GROUPLOAN03	0.6708	-0.0093	0.5522
	POVCRIT	0.9276	-0.0172	0.1448
	COLLATERAL	-0.9623	-0.0069	0.0716
	LOANSIZE03	-0.8810	0.1988	0.2461
	OSS03	-0.0882	0.9707	0.0802

Table 5: Correlation between factors

Year	Correlation factor 1 - factor 2
1999	-0.0102
2000	0.2168
2001	-0.1282
2002	0.2581
2003	0.1733

4. Cluster Analysis

In order to facilitate the understanding of the results obtained in the last section, we will now make use of a statistical procedure that allows to group objects based on the characteristics they possess, namely: cluster analysis. This technique allows the partitioning an original population into subsets (clusters), so that the data in each subset (ideally) share some common trait – proximity according to some defined distance measure. The goal is thus to bring together individuals having relatively similar characteristics, while individuals belonging to different groups are as disparate as possible. With the agglomerative hierarchical clustering method, the main steps of the groups' identification procedure are as follows. Let there be *n* observations (the 45 MFIs) with *m* characteristics (the two scores of performance). At the beginning, every observation is considered as a separate group. A similarity index – the Euclidean distance between the average scores of two clusters – is computed for all $n\cdot(n-1)/2$ potential pairs of observations and the two closest are grouped. In the next step, the same procedure is applied to the n-1 remaining clusters, which implies $(n-1)\cdot(n-2)/2$ distances. This process goes on until all observations belong to the same group, and hence creates a hierarchy of clusters.

This method leaves open the choice of the final number of clusters. Many stopping rules can help this decision and we will make use of two criteria, which are described as the best out of the thirty investigated by Milligan & Cooper (1985): the pseudo-t^2 and the pseudo-F.

Large values of the pseudo-F index indicate distinct clustering and one must therefore maximize this statistic. The opposite is true for the pseudo-t^2, and one should choose the number of clusters so that this index is low and has much larger values next to it. It is advisable to look for a consensus among the two statistics, that is, local peak of the pseudo-F combined with a small value of the pseudo-t^2 and a larger value of the latter for the next cluster fusion.

Applying this procedure to group the MFIs of our data set on the basis of the 2 scores we ascribed them through factor analysis and for each year gives the statistics displayed in Table 6, where the first 15 cluster groupings can be examined. Taking 1999 as an example, we see that the pseudo-F is maximized for 10 clusters, whereas the pseudo-t^2 is maximal for three groups, indicating the presence of four clusters. The solution of five clusters seems to be the best compromise, since the pseudo-F is quite low for four clusters but noticeably higher for five clusters. Applying the same reasoning to each year gives four clusters for 2000, 2002 and 2003 and five for 1999 and 2001.

For some years, the choice is not really clear and the *cluster trees* (or *dendrograms*) eased our decisions. The cluster tree in Figure 2 presents graphical information concerning which observations are grouped together at various levels of similarity for 2003. At the bottom of the dendrogram, each observation would be considered its own cluster. As one climbs up in the tree, observations are combined until all are grouped together, the height of the vertical lines indicating the similarity (or dissimilarity) of two groups. Creating four clusters tantamount to cutting the tree horizontally where it has only four branches. Since they are among the longest branches, it confirms that the four clusters we formed actually are very dissimilar.

Having determined the clusters, it is interesting to plot the scores one against the other to see how the groups are located. The representation for 2003 is provided in Figure 3. MFIs belonging to cluster 1 are located at the bottom-left corner, so that they are relatively ineffective along both dimensions of performance. The MFIs of cluster 2 perform well on the social dimension but not on the financial one. Inversely, cluster 4 is efficient according to the financial dimension but not to the social one. Finally, cluster 3 contains only one MFI, which is very effective on both dimensions. From this plot, one can see that the trade-off between outreach and sustainability is not obvious: in that case, MFIs should be situated along a line going from the top-left to the bottom-right.

These visual notings are confirmed by the figures contained in Table 7, that shows the average scores of the MFIs pertaining to the various clusters found in each year. The composition of groups is not very stable across year, but one could still try to discern some general pattern. For every year, there is one quite large cluster that scores negatively on both performance dimensions, even if it is much smaller for 1999 and 2001. The MFIs pertaining to this cluster are performing relatively bad on both dimensions. A second cluster manages well concerning the social dimension but scores negatively on the financial dimension, whereas a third one obtains a high score on the financial dimension but performs poorly on the social dimension. If these two groups were containing most of the MFIs of our dataset, we could conclude that some trade-off between outreach and sustainability does actually exist, but this is not the case for every year. Eventually, there is always a very small cluster (sometimes composed of only one MFI) that distinguishes itself from the others by its high scores on both dimensions.

Table 6: Statistics for determining the number of clusters

Number of clusters	1999		2000		2001	
	Pseudo-*F*	Pseudo-t^2	Pseudo-*F*	Pseudo-t^2	Pseudo-*F*	Pseudo-t^2
1	-	14.19	-	13.03	-	4.63
2	14.19	6.03	13.03	6.84	4.63	5.27
3	9.06	25.29	11.24	26.54	5.23	27.57
4	19.84	15.93	23.26	15.62	15.69	19.82
5	28.34	11.42	25.29	10.06	22.44	12.83
6	29.09	9.63	30.16	9.17	24.99	11.28
7	29.27	3.66	33.55	58.57	29.25	5.58
8	29.52	4.10	30.60	11.06	27.62	16.55
9	28.30	5.59	35.97	15.41	31.09	8.17
10	31.70	·	45.09	1.83	36.39	5.54
11	30.17	4.64	42.88	7.00	36.40	5.18
12	30.53	·	44.82	6.99	36.13	11.48
13	29.43	5.61	53.76	2.40	40.47	5.19
14	29.58	·	55.74	9.69	41.22	11.96
15	29.13	6.36	68.03	·	47.16	10.78
Number of clusters	**2002**		**2003**			
	Pseudo-*F*	Pseudo-t^2	Pseudo-*F*	Pseudo-t^2		
1	-	6.23	-	10.69		
2	6.23	12.82	10.69	38.49		
3	10.50	47.22	28.68	24.44		
4	32.63	20.89	21.65	16.95		
5	33.86	17.12	23.15	17.66		
6	44.91	20.23	31.64	5.72		
7	51.43	3.82	29.36	5.78		
8	48.60	4.39	27.03	27.51		
9	47.87	3.92	35.66	6.59		
10	46.67	14.30	39.54	3.17		
11	54.96	1.54	38.60	8.83		
12	51.90	121.93	45.01	4.94		
13	50.97	5.68	43.93	4.37		
14	53.96	5.61	43.40	1.85		
15	61.41	·	42.58	16.77		

Note: the dots (·) indicate that the pseudo-t^2 is not computable because of ties in the hierarchical cluster analysis.

Figure 2: Dendrogram for 2003 cluster analysis

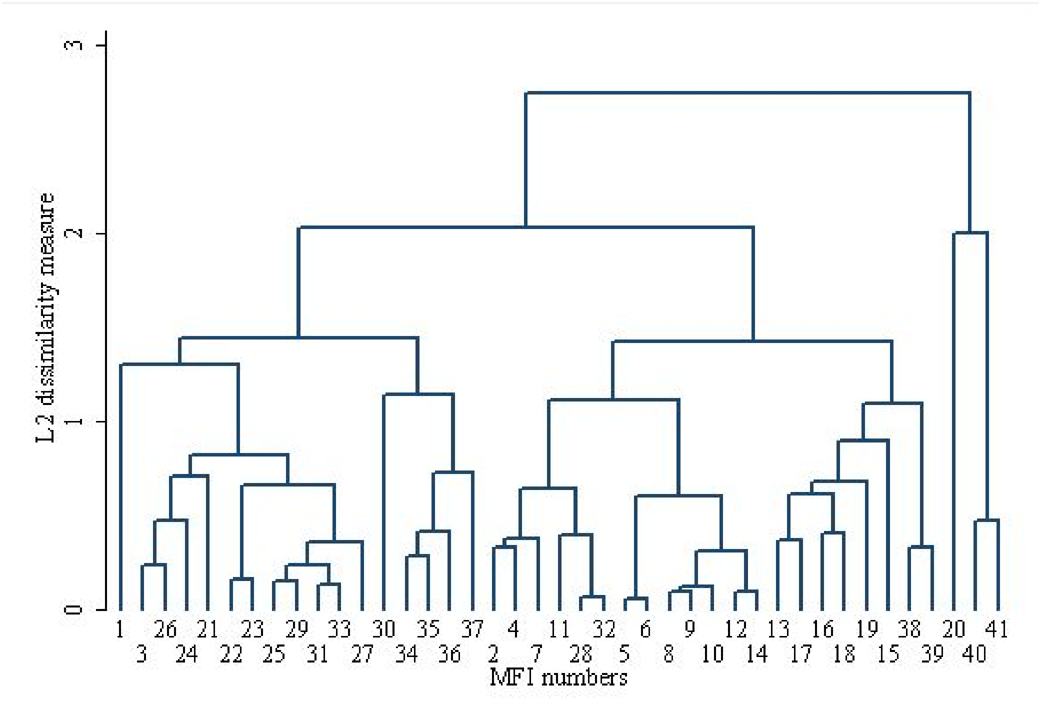
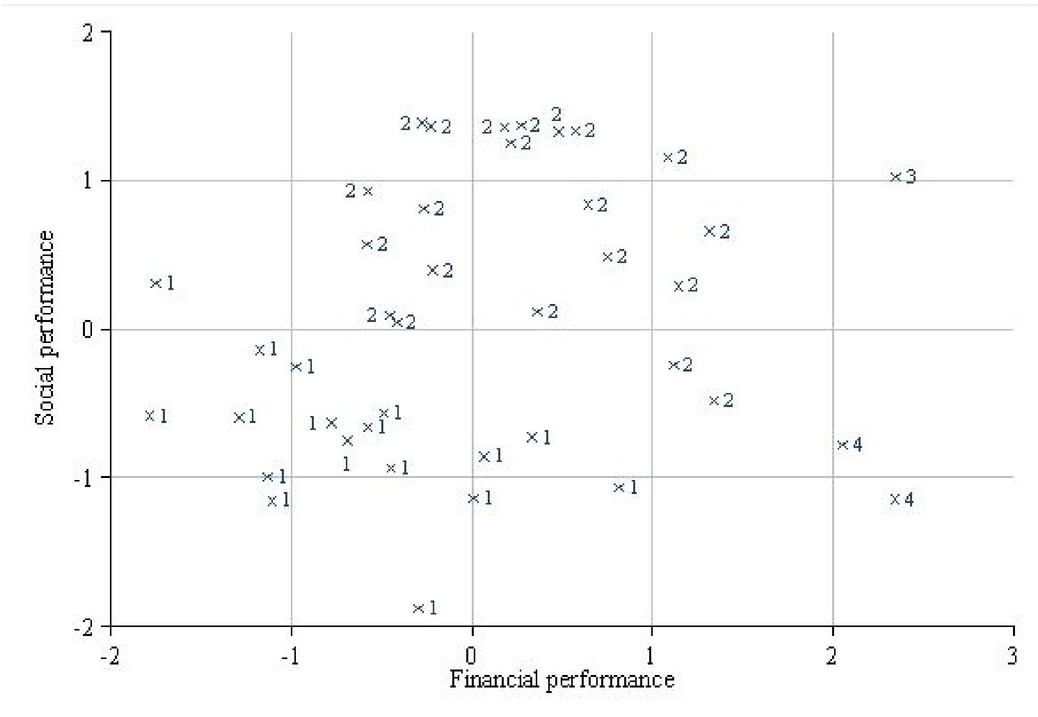


Figure 3: Scores and clusters for 2003



Note: Less than 45 MFIs appear in the Figures 3 and 4 because of missing values in the variables included in factor analysis.

Table 7: Mean Scores on the two Factors, by Cluster, 1999-2003

Year	Cluster number	Factor 1	Factor 2	Observations	%
1999	1	0.722	-0.579	11	35.48
	2	-0.213	-1.752	4	12.90
	3	-0.710	0.132	11	35.48
	4	1.226	1.214	4	12.90
	5	-0.667	2.015	1	3.23
	total	0.113	-0.163	31	100.00
2000	1	0.747	-0.204	16	45.71
	2	-0.609	-0.452	15	42.86
	3	-0.770	1.373	2	5.71
	4	1.200	2.335	2	5.71
	total	0.105	-0.075	35	100.00
2001	1	0.885	-0.541	14	37.84
	2	0.664	0.905	6	16.22
	3	-0.774	0.093	14	37.84
	4	-0.441	-1.872	2	5.41
	5	-1.037	2.295	1	2.70
	total	0.098	-0.062	37	100.00
2002	1	0.777	0.029	19	47.50
	2	-0.844	-0.695	15	37.50
	3	-0.499	1.530	5	12.50
	4	1.210	2.916	1	2.50
	total	0.038	0.017	40	100.00
2003	1	-0.742	-0.661	17	41.46
	2	0.716	0.308	21	51.22
	3	1.025	2.347	1	2.44
	4	-0.962	2.197	2	4.88
	total	0.037	0.048	41	100.00

5. Assessing what determines the performance

The scores ascribed to MFIs through factor analysis will now be used as the dependent variable of an equation. We will thus try to explain why some MFIs perform better than other.

Denoting the performance or score of MFI i on dimension j = 1, 2 by s_{ji}, we can posit the following regression model:

$$s_{1i} = x_{1i}\beta_1 + z_{1i}\gamma_1 + \varepsilon_{1i}$$
$$s_{2i} = x_{2i}\beta_2 + z_{2i}\gamma_2 + \varepsilon_{2i}$$

where x_i is a (row) vector of MFI i's characteristics that explain both its social and financial performance, while z_{ji} contains variables that are presumed to affect either its social or its financial performance. Based on the idea that both scores are inter-related by a possible trade-off, we here assume that: $E(\varepsilon_{1i}, \varepsilon_{2i}) = \sigma_{12} \neq 0$, which implies that the equations must be estimated with the seemingly unrelated regressions model (SUR)[2].

Deciding which variable belongs to either the x_i or z_{ji} vectors is not an easy task. We list in Table 8 candidate variables which may affect either or both scores. Again, this list is also limited by the number of observations available.

[2] One could also imagine that a system of simultaneous equations, whereby each score enters as an explanatory dependent variable, be estimated via three stage least squares. We do not pursue this route here, because of our very limited data set.

Table 8: Description of the variables used in the SUR model

Variable	Description
Services	Number of financial services offered by the MFI
Scale	Scale of operation (1 = small, 2 = medium, 3 = large)
NAC	Number of active clients in thousands, at the end of the year
Rural	Percentage of rural clients in 2003
LO/branch	Number of loan officers by branch
Ceiling	Interest rate ceiling (0 = no, 1 = yes)
First	Processing time for a first loan (days)
Competitors	MFI has competitors (0 = no, 1 = yes)
Clients/LO	Number of clients per loan officer in 2003

The number of financial services offered by the MFI affects the *scope* of outreach, but one can also presume that it will have an influence on its financial performance, although the direction of this influence is not a priori obvious[3]. The scale of operation (as measured by the size of the portfolio) is related to *breadth* of outreach, but it certainly also has an effect on the financial viability of the MFI, since too small a scale of operation will not be sufficient to cover fixed costs. For the same reason, we also include the number of active clients (*NAC*) in both performance equations.

The number of loan officers per branch is presumed to affect mainly outreach, since MFIs with more loan officers are able to deliver more credits per client, and therefore this ratio increases both *breadth* and *scope* of outreach.

We expect that the percentage of rural clients is a factor of *depth* of outreach, since more rural clients are notably poorer than their urban counterparts[4]. Providing credit facilities in rural areas is however usually more costly than in cities, and therefore we also include this variable in x_i.

All other variables listed should have direct effects on financial viability, but not necessarily on outreach.

The results of the SUR model are given in Table 9 for the year 2003[5].

A first comment should be made on the SUR method. As can be seen by the value of the Breusch Pagan χ^2 statistic, we cannot reject the hypothesis that the errors are not correlated across equations ($\sigma_{12} = 0$). In this particular instance therefore, OLS could have been used instead of a SUR model (the results of such regressions were very similar). Note also that some coefficients have the "wrong" sign. The variable *Services* in the social performance equation has a negative and significant coefficient. It has the correct sign in the second equation but is not significantly different from zero.

Also, the variables *NAC* and *scale* have opposite signs in each equation, with all coefficients significant at the 0.05 level. We were expecting these variables to have a similar impact on both scores. We can therefore attempt the following partial explanation. The number of active clients is a *direct* measure of breadth of outreach. Having more clients (with possibly small loans) also implies higher costs per client, which is detrimental to financial performance. The scale of operation is measured by the portfolio size, and could be associated with larger loans. This implies, all other things equal, that it reduces costs to the MFI, while it is associated with less outreach. The percentage of rural clients has a very sizeable and significant effect on outreach and a negative one on the financial score, so one should clearly take into account the fact that an MFI has a rural rather than urban clientele in valuing its performance.

Turning now to the variables that were included in the financial performance equation only, we see that all variables have the expected sign and are significant. The number of clients per loan officer has a positive and very significant impact, although quite negligible in value. This variable probably indirectly captures labor productivity or efficiency in the MFI. The number of competitors seems to have a strong negative influence on the financial performance, which

---

3 Offering saving deposits, for instance, can be costly to manage, but it is also a source of funds that can prove cheaper than alternatives. See Morduch (1999) for a discussion on the role of savings.

4 *Scope*, *depth*, *breadth*, and *length* of outreach are discussed in Schreiner (2002).

5 Results for the other years can be obtained from the authors. Since the number of observations is smaller for the years 1999-2002, the estimations are not as good. In addition, most of the covariates used in the SUR model were measured in 2003 and are therefore only proxies for the past years.

Table 9: SUR explaining multidimensional performance for 2003

Variable	Factor 1	Factor 2
Constant	1.2902***	0.8695*
	(0.3826)	(0.5198)
Services	−0.2518**	−0.2332
	(0.1172)	(0.1444)
Scale	−0.3760**	0.3470**
	(0.1510)	(0.1625)
NAC	0.3457***	−0.2675**
	(0.1121)	(0.1220)
Rural	0.4941***	−0.2025*
	(0.1089)	(0.1206)
LO/branch	0.2280**	
	(0.1022)	
Ceiling		−0.3805*
		(0.2314)
First		0.5670***
		(0.1076)
Competitors		−0.9773**
		(0.3994)
Clients/LO		0.5714***
		(0.1126)
R-squared	0.556	0.656
F-stat	9.74	8.8
Breusch-Pagan	0.729	
Observations	39	

Note: All continuous variables have been standardized: *LO/branch*, *NAC*, *Rural*, *First* and *Ceiling*.

*** Significant at the 0.01 level
** Significant at the 0.05 level
* Significant at the 0.10 level

seems quite plausible. An interest ceiling has the obvious effect of reducing the capacity to generate revenues from the lending activity, although here, the coefficient is just significant at the 0.10 level. The time requested for granting a first loan has a large and highly significant positive effect on the financial score. It seems therefore that a crucial aspect of financial sustainability could be the scrutiny of loan officers in granting credits.

We also experienced with other variables and specifications. We introduced for instance the ratio of the wage rate of loan officers to the minimum wage in the financial performance equation, but it turned out insignificantly different from zero. A similar result is found in Hartarska (2005). We also attempted various specifications to include the number of donors per MFI, the profit status, and dummy variable for MFIs being member-owned in the second equation but none was significant.

6. Conclusion

Microcredit is often promoted as an efficient tool to help the poor, since it is based on sound economic principles. Rates of return of small scale investments can be very high and explain why some people are ready to pay high interest rates in order to finance them. However, market failures and relatively high transaction costs can prevent a substantial part of these investments to be realized through private financial intermediaries, especially in remote rural areas. MFIs' ambition is to fill the gap. As discussed earlier, they can do so either by focusing on the poor and expanding their outreach, or they may prioritize their financial viability.

The goal of this paper was to provide some new empirical and methodological insights on this important subject. It is quite similar in spirit to Flückiger & Vassiliev (2006), where MFIs' "outputs" are measured and evaluated with respect to resources used in an efficient frontier context, but with different data and an alternative model. Our approach attempts to shed some light on the way the performance of MFIs can be evaluated in a multi-dimensional context. To this end, we have shown how factor analysis can help construct some synthetic indices of both *outreach* and *self-sustainability*. Several papers have shown how *outreach* itself can be judged upon various criteria. The same is true, though to a lesser extent, for the financial performance. Clearly, some ambiguity can arise as to the choice of variables that should be used to define these indices. One advantage of factor analysis is that no arbitrary weight needs to be ascribed to each variable, as the "data speak for themselves", in that the weights are computed from the correlation matrix of the chosen variables. One drawback of this technique is that it does not provide information of the absolute level of performance. Still, the possibility to point out the (relatively) best MFIs of a group is quite valuable.

Cluster analysis was mainly used to better grasp the possibility that some MFIs would form groups across the two scores. The clusters were not very compact and quite unstable across the years, probably also because MFIs come from different countries and are possibly influenced by institutional or macroeconomic factors specific to their countries. More data, especially within countries could provide a clearer picture of what is going on with our chosen dimensions of performance.

The final section was devoted to find possible determinants that could explain the positions of the MFIs with respect to both measures of performance. To this end, we estimated a SUR model for the year 2003. Most results were plausible, although we stress that the paucity of the data made it clear that their statistical reliability is rather limited and that they should, for this reason, be considered more for their heuristic value.

References

Conning, J. (1999), "Outreach, Sustainability and Leverage in Monitoring and Peer-monitored Lending", *Journal of Development Economics*, **60**(1), 51–77.

Flückiger, Y., & A. Vassiliev (2006), "Evaluation of Microfinance Institutions in Peru: An Application of Data Envelopment Analysis", to be published in Balkenhol, B. (ed.), *Microfinance and public policy: the case for subsidies*, McMillan.

Hamed, Y. (2006), "Microfinance and Public Policy: Overview of Survey Results", to be published in Balkenhol, B. (ed.), *Microfinance and public policy: the case for subsidies*, McMillan.

Hartarska, V. (2005), "Governance and Performance of Microfinance Institutions in Central and Eastern Europe and the Newly Independant States", *World Development*, **33**(10), 1627–43.

Milligan, G.W., & M.C. Cooper (1985), "An Examination of Procedures for Determining the Number of Clusters in a Data Set", *Psychometrika*, **50**(2), 159–79.

Morduch, J. (1999), "The Microfinance Promise", *Journal of Economic Literature*, **37**, 1569–1614.

Morduch, J. 2000), "The Microfinance Shism", *World Development*, **28**(4), 617–629.

Navajas, S., M. Schreiner, R.L. Meyer & C. Gonzalez-Vega (2000), "Microcredit and the Poorest of the Poor: Theory and Evidence From Bolivia", *World Development*, **28**, 333–46.

Olsson, U. (1979), "Maximum Likelihood Estimation of the Polychoric Correlation Coefficient", *Psychometrika*, **44**(4), 443–60.

Schreiner, M. (2002), "Aspects of Outreach: A Framework for Discussion of the Social Benefits of Microfinance", *Journal of International Development*, **14**, 591–603.

Zeller, M., & R.L. Meyer (eds). (2002), *The Triangle of Microfinance: Financial Sustainability, Outreach and Impact*, Baltimore, Maryland: The Johns Hopkins University Press.

Zeller, M., C. Lapenu & M. Greeley (2003), *Measuring Social Performance of Micro-Finance Institutions: A Proposal*, Tech. rept. Argidius Foundation and Consultative Group to Assist the Poorest (CGAP).

Cahiers de recherche du Centre de Recherche Appliquée en Gestion (CRAG) de la Haute Ecole de Gestion - Genève

CRAG – Centre de Recherche Appliquée en Gestion
Haute école de gestion - Genève
Campus de Battelle, Bâtiment F
7, route de Drize – 1227 Carouge – Suisse
✉ crag@hesge.ch
www.hesge.ch/heg/crag
✆ +41 22 388 18 18
🖷 +41 22 388 17 40

2006

- N° HES-SO/HEG-GE/C--06/1/1--CH
  Andrea BARANZINI
  Damien ROCHETTE
  "La demande de récréation pour un parc naturel
  Une application au Bois de Pfyn-Finges, Suisse"

- N° HES-SO/HEG-GE/C--06/2/1--CH
  Giovanni FERRO LUZZI
  Yves FLÜCKIGER
  Sylvain WEBER
  "A Cluster Analysis of Multidimentional Poverty in Switzerland"