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Cecilio Mar Molinero , Begoña Gutiérrez Nieto,
Carlos Serrano Cinca

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By

Begoña Gutiérrez Nieto
Departamento de Contabilidad y Finanzas
Universidad de Zaragoza
bgn@unizar.es

Carlos Serrano Cinca
Departamento de Contabilidad y Finanzas
Universidad de Zaragoza
serrano@unizar.es

Cecilio Mar Molinero
IOC
Universitat Politècnica de Catalunya
and
School of Management
University of Southampton
Cecilio.mar@upc.es
camm@soton.ac.uk

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Microfinance institutions and efficiency

Abstract

Microfinance Institutions (MFIs) are special financial institutions. They have both a social nature and a for-profit nature. Their performance has been traditionally measured by means of financial ratios. The paper uses a Data Envelopment Analysis (DEA) approach to efficiency to show that ratio analysis does not capture DEA efficiency.

Special care is taken in the specification of the DEA model. We take a methodological approach based on multivariate analysis. We rank DEA efficiencies under different models and specifications; e.g., particular sets of inputs and outputs. This serves to explore what is behind a DEA score.

The results show that we can explain MFIs efficiency by means of four principal components of efficiency, and this way we are able to understand differences between DEA scores. It is shown that there are country effects on efficiency; and effects that depend on Non-governmental Organization (NGO)/non-NGO status of the MFI.

Keywords: Microfinance, microcredit, DEA, multivariate analysis, efficiency.

Introduction

Microcredit is the provision of small loans to very poor people for self-employment projects that generate income. It is a new approach to fight poverty. In its heart are new financial institutions, often non-profit organisations, whose aim is to serve those people who would not have access to a loan from a traditional trading bank.

The fact that Microfinance Institutions (MFIs) tend not to operate in the same way as traditional banks does not mean that they are not interested in profitability and efficiency issues. However, existing tools to assess the performance of traditional banking institutions may not be appropriate within this new context.

How can we assess if a MFI is efficient? How should we compare MFIs? How far is existing knowledge on traditional financial institutions appropriate in order to understand the behaviour of MFIs? These are the issues that are addressed in the current paper.

The paper starts with a discussion of microcredit and its role in the fight of financial exclusion. Existing tools for the assessment of performance in MFIs are next reviewed and some lessons are drawn from this review. It is suggested that Data Envelopment Analysis (DEA) is an appropriate tool for the assessment of MFI performance. There is, however, an issue to be resolved: how should the DEA model be specified? Which inputs and which outputs should it contain? A methodological approach based on multivariate analysis is applied in order to select appropriate model specifications, understand the way in which the relative efficiency of a MFI is determined by the choice of model, and to produce a ranking of MFIs in terms of efficiency. The methodology is applied to the analysis of 30 Latin American microcredit institutions. This is followed by a comparison between the procedure here described and traditional methods based on ratio analysis. The paper ends with a concluding section that lists and discusses the findings.

Microcredit and Microfinance Institutions

It has long been argued that commercial banks have not provided for the credit needs of relatively poor people who are not in a condition to offer loan guarantees but who have feasible and promising investment ideas that can result in profitable ventures; Hollis and Sweetman (1998). Meeting this need is of interest to governments, charitable institutions, and socially responsible investors. New financial institutions have arisen that are in touch with the local community, that can obtain information about the loan taker at low cost, and that often are not only interested in profit but also on the creation of jobs, women' employment, development, and green issues. These new financial intermediaries, the MFIs, provide small loans to poor people who can offer little or no collateral assets. But the provision of such microcredit is not limited to not-for-profit organisations. Traditional financial institutions can, and often do, make loans to the deprived as part of a socially responsible investment policy.

The best known innovation arising from microfinance programs is peer group loan methodology, in which members accept joint liability for the individual loans made. This joint responsibility approach results in low levels of default, but there are other reasons for successful repayment rates: dynamic incentives, regular repayment schedules and collateral substitutes; Morduch (1999).

Microcredit institutions have mushroomed in countries with less developed financial systems. The Microcredit Summit Campaign formed by donors, policymakers and more than 2500 MFIs, claimed to have helped 41.6 million of the poorest people around the world by 31 December 2002 (Daley-Harris, 2003). Their goal is to reach 100 million of the world poorest families by 2005. Moreover, the United Nations declared 2005 as the Year of Microcredit.

According to Von Pischke (2002), modern microcredit evolved from its origins in the mid 1970s to the present day from some organisations that offered loans and savings to individuals at the margins of the financial markets. Some examples of microcredit initiatives are: FINCA and ACCION International, two US organisations whose area of activity is Latin America; the rural units of Bank Rakyat Indonesia (BRI), one of the few institutions that receive no subsidies; and Grameen Bank in Bangladesh, now acting in more than 50 countries.

Assessing microcredit institutions

Microcredit emerges as a new approach to fight poverty. But, is the money lent by MFIs efficiently managed? There is much literature on bank efficiency, but very little on microfinance efficiency. Should we assess microfinance institutions efficiency the way banks do, taking into account financial inputs and outputs? This tends not to be the case: Morduch (1999) observes that discussions on microcredit performance almost ignore financial matters.

Yaron (1994) suggested a framework, based on the dual concepts of outreach and sustainability, that has became popular in the assessment of MFIs performance; Navajas *et al*. (2000), Schreiner and Yaron (2001). Outreach accounts for the number of clients serviced and the quality of the products provided. Sustainability implies that the institution generates enough income to at least repay the opportunity cost of all inputs and assets; Chaves and González-Vega (1996). It is difficult to think of a sustainable MFI with poor financial management; Johnson and Rogaly (1997). Sustainability has two levels: operational and financial (see, for example CGAP, 2003).

Microfinance industry evolution stresses more and more the importance of financial viability. A set of performance indicators has arisen, and many of them have become standardized, but there is by no means general agreement on how to define and calculate them. A consensus group composed of microfinance rating agencies, donors, multilateral banks and private voluntary organizations agreed in 2003 some guidelines on definitions of financial terms, ratios and adjustments for microfinance (CGAP, 2003). The ratios fall into four categories: sustainability/profitability, asset/liability management, portfolio quality, and efficiency/productivity. These measures derive from the financial ratio analysis implemented in conventional financial institutions. In what follows, we will concentrate on efficiency ratios. Table 1 shows a list of 21 ratios issued by Microrate, used to assess the performance of MFIs and their definitions. These are grouped in terms of portfolio quality, efficiency and productivity, financial management, profitability, productivity and others. Table 2 shows the values of these ratios in 30 Latin American MFIs.

Table 1 and Table 2 about here

The efficiency/productivity ratios reflect "how efficiently an MFI is using its resources, particularly its assets and personnel" (CGAP, 2003). Thus, efficiency ratios compare a measure of personnel employed with a measure of assets. Institutions can choose as assets either average gross loan portfolio, or average total assets, or average performing assets. CGAP describes as performing assets "loans, investments, and other assets expected to produce income". Personnel may be defined as the total number of staff employed or the number of loan officers. In this paper we are going to use a different definition of efficiency, based on DEA, and we will compare traditional ratio based measures with DEA efficiencies. It will be shown that they are not the same thing, and that ratio analysis is no substitute for efficiency analysis as defined by the micro economic theory of production functions.

DEA efficiency and financial institutions

The efficiency with which financial institutions conduct their business has long been studied. Efficiency assessment is based on the theory of production functions. The standard definition of efficiency is due to Pareto-Koopman; see Thanassoulis (2001). There are two main approaches to efficiency assessment: parametric frontiers and Data Envelopment Analysis (DEA). Berger and Humphrey (1997) provide a comprehensive review of methods and models up to 1997. This subject has continued to interest researchers up to the present date; some recent papers on efficiency and financial institutions are Athanassopoulos (1997), Bala and Cook (2003), Brockett *et al*. (2004), Dekker and Post (2001), Hartman *et al*. (2001), Kuosmanen and Post (2001), Luo (2003), Pille and Paradi (2002), Paradi and Schaffnit (2003), Pastor *et al*. (1997), Saha and Ravisankar (2000), Seiford and Zhu (1999), and Worthington (2004). The literature continues to grow all the time.

One advantage of DEA (nonparametric) over parametric approaches to measure efficiency is that this technique can be used when the conventional cost and profit functions cannot be justified; Berger and Humphrey (1997). DEA performs multiple comparisons between a set of homogeneous units. For an introduction to the theory of DEA see Thanassoulis (2001), Charnes *et al*. (1994), or Cooper *et al*. (2000).

For the purposes of this paper, it will be useful to make a distinction between model and specification in a DEA context. Different philosophical approaches as to what a financial institution does, and what is meant by efficiency lead to different models; see Berger and Mester (1997) for a full discussion. Two basic models are prevalent in the literature: intermediation and production; Athanassoupoulos (1997). Specification will refer to a more restricted concept: the particular set of inputs and outputs that enter into model definition.

Under the intermediation model, financial institutions collect deposits and make loans in order to make a profit. Deposits and acquired loans are considered to be inputs. Institutions are interested in placing loans, which are traditional outputs in studies of this kind; see, for example Berger and Humphrey (1991). Under the production model, a financial institution uses physical resources such as labour and plant in order to process transactions, take deposits, lend funds, and so on. In the production model manpower and assets are treated as inputs and transactions dealt with -such as deposits and loans- are treated as outputs. See, for example, Vassiloglou and Giokas (1990), Schaffnit *et al*. (1997), Soteriou and Zenios (1999).

We notice that the selection of inputs and outputs is determined by our understanding of what a financial institution does. Deposits provide an extreme example: they are inputs from an intermediation point of view, and outputs from a production point of view. The specification of what is an input and what is an output is crucial in the modelling process. In our particular case we do not need to ponder about the way in which deposits should be treated, since microfinance institutions do not always collect them, and had to be excluded as a possible variable in the data set since the technique to be applied, DEA, requires homogeneous data for all the MFIs. Many MFIs obtain funds from the market (loans) or receive grants. Other issues become relevant in the selection of inputs and outputs. For example, some MFI receive subsidised loans at an interest rate that is below the market.

It follows that the selection of inputs and outputs is crucial in the financial institution modelling. Berger and Humphrey (1997) suggest that one could assess efficiency under a variety of output/input specifications, and see the way in which calculated efficiencies change as the specification changes. This is sensible, but they do not provide guidelines on how to choose between specifications. In fact, specification searches are common in the modelling of financial institutions; examples are Oral and Yolalan (1990), Vassiloglou and Giokas (1990), and Pastor and Lovell (1997).

A major problem with the selection of inputs and outputs in a DEA model is that there is no statistical framework on which significance tests can be based. The neat approach of variable selection that is used in regression, based on t statistic values, has no parallel in DEA. One may be tempted to use as many inputs and outputs as one may think to be relevant, but some of them will be correlated, perhaps highly so. Parkin and Hollingsworth (1997) review the problems that variable selection creates in DEA. Jenkins and Anderson (2003) warn against the use of correlated inputs and outputs in a DEA model. An important issue is that the number of 100% efficient units increases with the number of inputs and outputs in the model, and adding irrelevant variables may change the results obtained; Dyson *et al*. (2001), Pedraja Chaparro *et al*. (1999). Specification search methods in DEA have been proposed by Norman and Stocker (1991), Pastor *et al*. (2002), and Serrano Cinca and Mar Molinero (2004).

Here we will use the model specification methodology suggested by Serrano Cinca and Mar Molinero (2004). This, in essence, consists in calculating efficiencies for every possible combination of inputs and outputs. A two way table is obtained in which the columns are output/input specifications and the rows are decision units (MFIs). The entries in the table are the efficiencies obtained under each different model for each MFI. The rows of this table are treated as cases and the columns as variables in a bivariate statistical analysis which throws light on the similarity between models, extreme observations, and the reasons why a particular

MFI achieves a particular level of efficiency with a particular specification. This will be discussed in detail in the empirical example presented below.

Microfinance in Latin America

Most of the research on banking efficiency has concentrated on US and developed countries. So far, neither DEA nor other parametric or non-parametric frontier techniques have been used to evaluate the efficiency of microfinance institutions. Here we depart from this trend, and analyse thirty Latin American MFIs from Bolivia, Colombia, Dominican Republic, Ecuador, Mexico, Nicaragua, Peru and Salvador. Some of them are for profit institutions and others are not profit oriented. Some MFIs are just specialised banking institutions, while others are Non-Governmental Organisations (NGOs). The question arises of whether this difference influences efficiency, or the way in which efficiency is achieved.

According to Miller (2003), some of the most experienced, developed, and diverse MFIs around the world can be found in Latin America. Using 2001 and 2002 data from 124 worldwide MFIs (provided by the MicroBanking Bulletin), almost half of them from Latin America, the author draws several conclusions: MFIs from this region have more assets, are more leveraged, and make use of an increasingly growing share of commercial funds than institutions from other regions. Lapenu and Zeller (2002) complete this vision: comparing African, Asian and Latin America MFIs, they find that the number of institutions and the number of clients remain small in Latin American MFIs compared to Asian. However, Latin American MFIs mobilise a good amount of savings and loans in comparison to Asian MFIs. Finally, Latin America records the largest volume per transaction although rural outreach remains low.

For the purposes of this paper, data was obtained from Microrate web page for the year 2003, and completed with the Technical Guide prepared by Jansson *et al*. (2003). All the data is measured in monetary units (thousand of dollars), except the number of credit officers and the number of loans outstanding.

Selection of inputs and outputs

The selection of inputs and outputs in the model was based on Yaron's (1994) outreach and sustainability framework. The number of loans outstanding (output) and the gross loan portfolio (output) were selected as measures of outreach. The two aspects of sustainability, operational and financial, guided the selection of a further input and output. Interest and fee income (output) was taken as an indicator of operational sustainability, as a MFI that fails to collect enough income is not viable in the long term. Financial sustainability was captured through operating expenses. In essence, the collection of fee and interest income is necessary for survival, but such survival cannot be long lasting if this income is collected at high cost. In common with other similar studies, the number of credit officers was also used as an input.

The inputs selected in this study are credit officers and operating expenses. A production model would suggest the inclusion of the first input, while the second input is consistent with an intermediation model. Jansson *et al*. (2003) define loan officers as "personnel whose main activity is direct management of a portion of the loan portfolio". Our choice of input could have been total staff, but this would have included people whose activity is unrelated to the MFI activity. The number of employees has been proposed as an input by Berger and Humphrey (1997), Dekker and Post (2001), Desrochers and Lamberte (2003), Leon (1999), and Tortosa-Ausina (2001) among others. Operating expenses –or similar inputs have been suggested by Berger and Humphrey (1997), Cuadras-Morató *et al*. (2001), Laeven (1999), Pastor (1999) and Worthington (1998). Operating expenses are "expenses related to the operation of the institution, including all the administrative and salary expenses, depreciation and board fees"; Jansson *et al*. (2003).

The selection of outputs is also consistent with the production and intermediation models. Interest and fee income and the gross loan portfolio are associated with an intermediation orientation, whereas the number of loans outstanding is associated with a production orientation. We wish to emphasize that the gross loan portfolio and the number of loans outstanding appeared as components of MFI efficiency ratios in Table 1. Interest and fee incomes are used by Pastor (1999). Gross loan portfolio or similar measures are often mentioned: Berger and Humphrey (1997), Desrochers and Lamberte (2003), Laeven (1999), Lozano-Vivas (1998), Leon (1999), Tortosa-Ausina (2001), and Worthington (1998). Finally, the number of loans outstanding is mentioned by Berger and Humphrey (1997), Budnevich *et al*. (2001) and Tortosa-Ausina (2001). As there is some difficulty in getting data for the number of loans processed in a given period, we use instead the stock of loans. Table 4 gives the values of inputs and outputs for the MFIs in the sample[1].

Table 3 about here

Table 4 about here

Specifications and DEA efficiencies

Notation is needed to simplify the discussion of the various specifications. Inputs are referred to by means of capital letters, in such a way that the first input (credit officers) is represented by the letter A, and the second input (operating expenses) by the letter B. Outputs are referred to by means of numbers. The first output (interest and fee income) is associated with number 1, the second output (gross loan portfolio) with number 2, and the third output (number of loans outstanding) with number 3. In this way a specification that treats a MFI as an institution whose credit officers (input A) take interest and fee income (output 1) and place a number of loans in the market (output 3) would be labeled A13. If this specification is augmented with operating expenses (input B) and gross loan portfolio (output 2), the specification becomes AB123. An intermediation model would be described by a specification such as B2. Under the specification B2, a MFI is an institution that spends money to build a loan portfolio. Of course, this is just a performance indicator, EP1 in Table 1, relating operating expenses to gross loan portfolio, contained in the list recommended by the consensus group of rating agencies, donors, banks, and voluntary organizations.

Other views of the way in which a MFI operates can be generated by using different combinations of inputs and outputs. Efficiency ratios are a particular case obtained when only one input and only one output enter into the specification. It is, of course, possible to think of all possible combinations of inputs and outputs. The total number of possible specifications with two inputs and three outputs is 21. The complete list of specifications can be seen in Table 5.

DEA efficiencies for each MFI were calculated using the CCR model of constant returns to scale; Charnes, Cooper, and Rhodes (1978). The results are given in Table 5.

Table 5 about here

Visual examination of Table 5 reveals some important features. Two MFIs (W-Popayan, an NGO and Findesa, a non-bank financial institution) are 100% efficient under many specifications. On the other side, some MFI achieve low scores under most specifications. No MFI is efficient under all specifications, highlighting the fact that the selection of inputs and outputs and, therefore, the view of what constitutes efficiency in this sector is a matter of importance. If we take, for example, W-Popayan, we find that it is 100% efficient under 18 specifications, meaning that it is an excellent institution, but its efficiency drops below 30% under A1, A2 and A12. We conclude that W-Popayan is good in any specification that contains either input B or output 3, indicating that this MFI is good at generating lots of loans with low operating expenses. A counter example is Fie, a non-bank financial institution, whose scores tend to be low, but becomes 100% efficient under 4 specifications: AB12, AB123, AB2, AB23. This indicates that, although Fie can take action to improve its efficiency, it has some strong points that deserve further attention.

In summary, the level of efficiency achieved by a particular MFI depends on the specification chosen, indicating that specification search is delicate and important. In addition, if two MFIs achieve the same efficiency score under a given specification they may do so following very different patterns of behaviour: there is no single path to efficiency in MFI. Exploring what is behind a DEA score is the objective of the next sections.

Multivariate analysis of DEA efficiency results

Serrano Cinca and Mar Molinero (2004) propose a specification search methodology based on treating the data in Table 5 as a multivariate data set. Other examples of the use of this approach are Serrano Cinca *et al.* (2004a), and Serrano Cinca *et al.* (2004b). This involves treating specifications as variables and MFIs as cases in a Principal Components Analysis (PCA). For an account of PCA see, for example, Chatfield and Collins (1980).

The first principal component, accounting for 57% of the variance, has an associated eigenvalue of 12.1; the second component accounts for a further 18% of the variance with an associated eigenvalue of 3.8; the third component, in turn accounts for 15% of the variance with an eigenvalue of 3.1; finally, there is only one more eigenvalue greater than 1, at 1.3, accounting for 6.4% of the variance. In total, the first four principal components account for 97% of the variance. This suggests that only four numbers (components) are required to explain why a particular MFI achieves a certain level of efficiency under all specifications.

Component correlations are shown in Table 6. It can be seen that the first principal component (PC1) is positively and highly correlated with efficiency under all specifications, suggesting that it provides an overall measure of efficiency that could be seen as an average over all specifications. The meaning of the remaining components could be assessed in the same way, just looking at the values in the columns in Table 6, but we prefer a more graphical approach to interpretation based on component scores. Each MFI is associated with four components, and this forces us to work with projections on to pairs of components. Component scores for each MFI in principal components 1 and 2 can be seen in Figure 1, and component loadings in principal components 2 and 3 can be seen in Figure 2.

Table 6 about here

Figure 1 about here

Figure 2 about here

If we look at Figure 1 while taking into account the numbers in Table 5, some interesting features appear. W-Popayan, Findesa, C-Cusco, that are efficient under many specifications, appear at the right hand side of the figure. At the other extreme of the figure we find MFIs such as Cr-Arequipa and Fincomun, that achieve low levels of efficiency under most specifications. This is in line with our observation that the first principal component provides an overall rating in terms of efficiency. We could approach the understanding of the remaining components in a similar vein. For example, the second component appears to be associated with Non-Governmental Organisation (NGO) status, as all the MFIs with a positive score in this component are NGOs, and all the MFIs with a negative value of the component, with the exception of Nieborowski, are non-NGOs. Towards the top of Figure 2 we find MFIs whose efficiency is higher under specifications that contain input A (credit officers) than under specifications that contain input B (operating expenses). The most extreme example is Findesa. Findesa is 100% efficient under all models that contain input A, but its efficiency drops considerably when this input is excluded. This would suggest that the third principal component is associated with the efficient use of input A versus the efficient use of input B. However, it is dangerous to perform this type of labelling exercise without the help of a formal tool. In order to interpret the meaning of the components and in order to highlight the information contained in the figures, we resort to the technique of Property Fitting (Pro-Fit).

Pro-Fit is a regression-based technique that draws lines in the figures in much the same way in which North-South directions are drawn in order to orient a geographical map. A particular characteristic of a MFI is taken as a property. A line is drawn pointing in the direction towards the value of the property increases. For example, in Figure 1, if we calculate the efficiency of the various MFIs under specification B3, we find that W-Popayan is associated with the highest value, while Fincomun and Bancosol show the lowest values. B3 efficiency takes intermediate values in the remaining MFIs, increasing as we approach W-Popayan and decreasing as we approach Bancosol. Thus, a line from the origin towards W-Popayan, and away from Bancosol, would provide an indication of how B3 efficiency changes within Figure 1. A good introduction to Pro-Fit can be found in Schiffman *et al.* (1981). For some examples of the use of Pro-Fit within a management science context see Mar Molinero and Serrano Cinca (2001) and Serrano Cinca *et al* (2004a).

Pro-Fit lines have been calculated for all the specifications and displayed in Figures 1 and 2. Goodness of fit statistics associated with the Pro-Fit lines is given in Table 7. Figures 1 and 2 will now be interpreted in the light of the information contained in the directional vectors.

Table 7 about here

The first principal component has already been identified as an overall measure of efficiency that summarises all the models. This can be clearly seen in Figure 1, where all the lines associated with the different specifications are at acute angles with the horizontal axis, indicating positive correlation between the value of the first component score for each MFI and efficiency, in whatever specification efficiency is measured. In Figure 1, the label "global efficiency" has been attached to the first component.

The second principal component has been already interpreted as being related to NGO status, and this is clear in Figure 2 where the shaded area contains all the MFIs with NGO status.

We observe in Figure 2 that specifications that contain input A in their definitions are associated with directional vectors that point upwards, while specifications that contain input B in their definition are associated with downward pointing directional vectors. The third principal component clearly reflects the different strategies followed by MFIs in their search for efficiency, opposing those that follow a policy of being efficient in the use of credit officers- positive values of the third principal component- and those that follow a policy of being efficient in their operating expenses – negative values of the third principal component. In Figure 2 we also see that Findesa can be considered to be a discordant observation. Indeed, Findesa is an extreme case of performance related pay, since 99% of credit officers' salary is due to incentive pay, and this is reflected in our results.

Principal Component 4 was found to be associated with input 2- gross loan portfolio. Specifications that contain output 2 in their definition produce vectors that point towards the negative end of the fourth principal component, while specifications that exclude this output produce vectors that point towards the positive side. This is sending the message that the inclusion or exclusion of this output affects efficiency values.

In summary, when describing a MFI from the point of view of efficiency, we need to refer to at least four characteristics, or principal components of efficiency. The first principal component refers to an overall assessment of efficiency under all possible models, and gives a ranking of MFIs. The second component refers to the NGO status. The third principal component is associated with inputs and reveals which MFIs have an approach to efficiency based on credit officers, and which ones approach efficiency by concentrating on operating expenses. The fourth principal component is associated with the inclusion or exclusion of an output in the model: gross loan portfolio.

Returning to the difference between W-Popayan and Findesa, that was earlier mentioned, we are now in a position to see in which way these two institutions are different. In Figure 1 we see that both W-Popayan and Findesa are at the extreme right hand side of the first principal component, indicating that both are fully efficient in an overall assessment. W-Popayan, is towards the top of this figure, at the extreme of vector A3, indicating that W-Popayan places a high number of loans per credit officer, while Findesa is at the extreme of vector B1, indicating that with little operating expenses obtains a great deal of interest and fee income. But is in Principal Component 3 where the difference appears most clearly. W-Popayan is at the bottom of Figure 2 indicating efficient use of credit officers, while Findesa is located towards the top of the same figure, indicating efficient use of operating expenses. Both W-Popayan and Findesa achieve similar scores with respect to Principal Component 4.

Non-governmental organisations and country effect

Two aspects of MFIs will now be examined: their country of operation, and their non-governmental (NGO) status. We will start with the NGO status.

Given the aims and objectives of MFIs - the fight against poverty, self-help, and the promotion of women's status -, it is not surprising to discover that many of them are NGOs. In fact, very often an organisation starts as an NGO, and when it becomes well established in the microfinance world, changes into a non-banking financial institution. But are NGOs more or less efficient than non-NGOs MFIs? Is there anything in the way they achieve efficiency that distinguishes them?

A region has been highlighted in Figure 2. This region contains only NGO institutions and does not contain any institution that is not NGO. MFIs outside this region are all non-NGOs. It is clear that, from the point of view of efficiency there is something that distinguishes a NGO MFI. Looking further into Figure 2, we see that the profit line B3 points directly towards the cluster of NGO MFIs and away from the rest of the MFIs. This suggests that NGOs try to make a large number of loans and operate as cheaply as possible. This is very much in tune with this type of organisation, since they tend to be operated by volunteers to keep costs down, and aim at supporting as many individuals as possible. The specifications that are most in tune with non-NGO institutions are A1, A12, and A2. Non-NGOs, therefore, rely on their specialised staff to build a profitable portfolio of loans, very much like commercial banks would do. The difference is not in the way they view the financial business but in their attitude towards obtaining guarantees for their loans and, indeed, in the average size of loans. It is to be noticed that the most extreme point in the non-NGO region of Figure 2 is Bancosol, a commercial bank that is involved in the microfinance business.

We now turn our attention to the country effect. There is a country effect, best seen in Principal Component 4. Figure 3 plots component scores in principal component 1 versus principal component 4. The names of the MFIs have been replaced with the names of the countries in which MFIs operate. We can see that there is very little overlap between the countries. From top to bottom, all Nicaraguan MFIs appear together; all but one Peruvian MFIs appear together; all but one Colombian MFIs appear together; and all Bolivian MFIs appear together. Nothing can be said about Salvador, Ecuador, and the Dominican Republic, since these countries are represented by just one MFI each. There is no right to left grouping of countries in Figure 3, indicating that country of origin and overall efficiency are unrelated.

Remembering that Principal Component 4 is associated with output 2 (gross loan portfolio), one would conclude that efficiency of MFIs in Bolivia is associated with building large portfolios, while efficiency of MFIs in Nicaragua has to be assessed in terms of the number of loans or the amount of interests and fees collected by the MFI. In fact, Bolivia has one of the more developed microfinance markets, where margins are narrowing and this is resulting in mergers and acquisitions within the MFI industry, Silva (2003).

Figure 3 about here

DEA efficiency and ratio analysis

Up to now we have been working with DEA efficiency. We have been able to rate MFIs in terms of overall DEA efficiency; we have seen that there are effects associated with NGO status; and we have observed country effects. The question remains of what the DEA analysis adds to our knowledge of microfinance institutions? Have we observed effects that would have remained hidden if we had used traditional ratio analysis? This will be the object of the current section.

Traditional ratios used to assess a MFI institution have been discussed in a previous section, their definitions given in Table 1, and their values are shown in Table 2.

It is clear that there is redundancy in a set of 21 ratios, and that it should be possible to use a smaller number of factors in order to describe what is special about a given MFI. For this reason, ratios have been treated as variables and MFIs as observations and principal component analysis has been performed. Seven principal components were found to be associated with eigenvalues greater than one, accounting for 79% of the total variance in the data.

We have now reasoned as follows. Seven factors are needed to describe a MFI from the point of view of ratio analysis. Some of these factors are probably related to efficiency, in whatever form this is defined. Indeed, ratios EP1 to EP4 are known in the trade as "efficiency and productivity ratios". If efficiency is captured by the ratios, there will be at least one principal component that reflects efficiency. Of course, this definition of efficiency does not have to coincide with DEA efficiency, but one expects that if a MFI is efficient from the point of view of ratio analysis, it will also be efficient from the DEA point of view. The fact that some DEA specifications coincide with ratio definitions make us think that the two approaches will be related. But in this paper we have shown how to define a measure of overall efficiency taking into account all possible specifications. Does ratio analysis capture in any way such measure of overall efficiency?

To answer this question we have computed Pearson correlation coefficients between component scores obtained from the ratios in Table 2, and principal components obtained from efficiency scores in Table 5. These are summarised in Table 8.

Table 8 about here

We can see in Table 8 that the first DEA principal component, the measure of overall efficiency, is significantly correlated with the second and the third principal components of the ratios. The second DEA principal component, NGO status, is associated with the first principal component of the ratios. The third DEA principal component, which in our case is related to efficient use of inputs, is not reflected in the principal components of the ratios. Finally, the fourth DEA principal component, which is associated with the country effect, is correlated with the second and the third principal components of the ratios. If we look at component correlations, not shown here, we find that the first principal component of the ratios is correlated with EP3 (number of borrowers per staff), EP4 (number of borrowers per credit officer), FM3 (debt/equity ratio), O1 (average loan balance per client) and O3 (equity/assets ratio); the second principal component of the ratios is correlated with EP1 (operating expense ratio), FM1 (funding expense ratio), FM2 (cost of funds ratio), and Prd1(Personnel expense/average gross portfolio). Of all efficiency ratios, only EP1 appears to be associated with the overall measure of DEA efficiency, and its effect is relatively low, as the correlation of EP1 with the first principal component of the ratios is 0.75, and the correlation of the second principal component of the ratios with the first principal component of DEA efficiencies is -0.53. We have to conclude that efficiency and productivity ratios are only vaguely related to efficiency from the DEA point of view. What are we to conclude? DEA efficiency is well based on Economic Theory, while ratios are only consensus indicators. Everyone can make up his/her own mind, but we lean towards DEA efficiency.

Conclusions

DEA has long been applied to the measurement of financial institutions efficiency. Here we have used it to assess efficiency of MFIs, which have a banking side and a social side. We have suggested a methodological approach that goes behind a DEA measure and explains the scores obtained under different choices of models and specifications.

We have obtained DEA efficiencies for every combination of inputs and outputs of 30 Latin American MFIs. This way, we can see that the level of efficiency achieved by a MFI depends on the specification chosen. So the choice of a particular model or specification is relevant for efficiency assessment.

We have then followed a multivariate approach on efficiencies obtained through DEA: we have combined Principal Component Analysis with Property Fitting. We have obtained four principal components of efficiency, each one related to a different issue: overall efficiency, NGO status, input choice and output choice. This way we can understand why a MFI achieves a level of efficiency under a given specification, or which are the paths to efficiency followed by a group of MFIs.

Finally, there is no reason why we should be fanatic believers in a DEA efficiency world, but the converse is also true. Efficiency and productivity ratios that have emerged from the deliberations of a committee need not be associated with efficiency nor with productivity. We have shown that our approach to efficiency analysis not only produces an overall ranking of MFIs in terms of the use they make of inputs and outputs, but also reveals features that distinguish NGOs from non-NGO institutions, that we can explain the reasons why some MFIs are or are not efficient, and that there are country effects in the data.

We finish by encouraging analysts, rating agencies, and users to go beyond ratio analysis in MFIs and incorporate measures of efficiency based on Data Envelopment Analysis.

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PQ1 portfolio at risk = portfolio at risk / gross loan portfolio
PQ2 provision expense ratio = loan loss provision expense / average portfolio
PQ3 risk coverage ratio = loan loss reserves / portfolio at risk
PQ4 write-off ratio = write offs / average portfolio
EP1 operating expense ratio = operating expenses / gross loan portfolio
EP2 cost per client = operating expenses / average number of clients
EP3 personnel productivity = number of borrowers per staff
EP4 credit officer productivity = number of active borrowers / number of credit officers
FM1 funding expense ratio = interest and fee expense / average gross portfolio
FM2 cost of funds ratio = interest and fee expenses on funding liabilities / average funding liabilities
FM3 debt/equity ratio = total liabilities / total equity
P1 return on equity = net income / average equity
P2 return on assets = net income/ average assets
P3 portfolio yield = cash financial revenue / average gross portfolio
Prd1 personnel expense/average gross portfolio
Prd2 credit officers/total personnel
Prd3 incentive pay as % of base salary
Prd4 percent of staff with <12 months
O1 average loan balance per client
O2 current assets/current liabilities
O3 equity/assets

Table 1. The 21 ratios and their definitions

PQ: Portfolio Quality; EP: Efficiency and Productivity; FM: Financial Management; P: Profitability; Prd: Productivity; O: Other

DMU	PQ1	PQ2	PQ3	PQ4	EP1	EP2	EP3	EP4	FM1	FM2	FM3	P1	P2	P3	Prd1	Prd2	Prd3	Pr4	O1	O2	O3
Adopem	0.037	0.02	1.025	0.002	0.155	387.789	226	431	0.047	0.136	0.8	0.007	0.003	35.7	0.076	0.526	0.8	0.229	191	4.7	0.509
Andes	0.06	0.035	1.161	0.014	0.137	189.492	69	248	0.026	0.054	10	0.33	0.03	0.258	0.087	0.276	0.237	0.162	1451	1.9	0.086
Bancosol	0.12	0.045	0.726	0.013	0.132	210.876	74	239	0.028	0.054	5.6	0.049	0.007	0.223	0.068	0.311	0.389	0.222	2008	2.1	0.148
Calpia	0.031	0.034	1.393	0.003	0.19	205.556	136	360	0.018	0.04	5	0.17	0.028	0.276	0.091	0.377	0.41	0.27	1122	1.9	0.143
C-Arequipa	0.061	0.032	1.122	0.005	0.135	148.869	129	336	0.037	0.064	5.2	0.547	0.08	0.393	0.073	0.384	0.11	0.231	1122	1.2	0.148
Cr-Arequipa	0.057	0.034	0.99	0.011	0.248	203.063	48	91	0.058	0.127	4.2	0.264	0.054	0.487	0.134	0.526	0.5	0.447	825	5.7	0.187
C-Cusco	0.048	0.015	1.173	0.001	0.123	1560.900	129	400	0.031	0.054	5.2	0.593	0.085	0.356	0.073	0.323	0.11	0.157	1333	1.2	0.155
C-Ica	0.169	0.001	0.876	0	0.173	1500.884	91	237	0.041	0.077	3.9	0.325	0.058	0.349	0.091	0.385	0	0.291	761	1.3	0.193
Compartamos	0.01	0.028	5.128	0	0.391	113.787	182	317	0.064	0.155	1.7	0.61	0.21	1.016	0.262	0.573	0.5	0.421	292	2.8	0.341
Confia	0.017	0.054	1.644	0	0.217	1909.873	99	256	0.075	0.132	6.3	0.498	0.059	0.49	0.125	0.385	0.65	0.296	890	1.3	0.13
Confianza	0.048	0.053	0.863	0.018	0.235	2090.002	133	287	0.06	0.108	4.2	0.181	0.036	0.513	0.113	0.463	0.12	0.244	894	3.5	0.182
C-Sullana	0.87	0.022	0.993	0.017	0.182	99.262	83	253	0.061	0.111	5.2	0.352	0.055	0.42	0.083	0.328	0.12	0.308	565	1.4	0.154
C-Tacna	0.061	0.012	0.883	0.001	0.167	169.844	61	166	0.062	0.092	5.2	0.316	0.052	0.398	0.079	0.366	0.123	0.26	1004	1.3	0.154
Cr-Tacna	0.094	0.007	0.941	0.01	0.223	2026.796	74	166	0.039	0.091	2.9	0.216	0.051	0.39	0.13	0.444	0	0.244	904	3.2	0.241
C-Trujillo	0.052	0.028	0.94	0	0.159	134.940	68	192	0.038	0.074	5.8	0.441	0.067	0.367	0.079	0.354	0.054	0.326	885	1.3	0.141
Diaconia-Frif	0.155	0.059	0.38	0.001	0.142	65.232	194	408	0	0	0	0.062	0.06	0.297	0.086	0.475	0	0.288	465	48.8	0.982
D-Miro	0.009	0.016	1.885	0	0.322	97.713	157	421	0.019	0.062	0.6	0.171	0.119	0.607	0.186	0.374	0.64	0.505	310	2.3	0.581
Edyficar	0.075	0.022	0.851	0.051	0.226	214.961	92	274	0.037	0.097	3	0.205	0.047	0.399	0.137	0.335	0.076	0.36	961	1.8	0.233
Fie	0.069	0.058	1.263	0.015	0.114	149.430	98	242	0.027	0.063	6.3	0.156	0.021	0.24	0.065	0.405	0.515	0.3	1318	2.5	0.13
Finamerica	0.113	0.02	0.29	0.004	0.198	165.682	90	257	0.046	0.083	5.9	-0.36	-0.049	0.271	0.103	0.350	0.144	0.228	833	1.3	0.136
Fincomun	0.036	0.023	1.004	0.016	0.849	502.138	54	134	0.074	0.073	3.7	-0.019	-0.003	0.934	0.565	0.398	0.67	0.301	573	1.4	0.196
Findesa	0.02	0.034	0.87	0.005	0.224	265.590	114	489	0.094	0.203	4.2	0.152	0.032	0.506	0.139	0.232	0.99	0.242	1147	14.5	0.187
Nieborowski	0.036	0.039	0.729	0.005	0.151	1011.806	97	239	0.038	0.08	2.7	0.803	0.215	0.571	0.081	0.407	0.8	0.267	670	4.6	0.258
Proempresa	0.105	0.07	0.794	0.012	0.269	238.407	107	292	0.053	0.108	3.6	0.05	0.011	0.498	0.129	0.368	0.032	0.338	889	2.8	0.208
Pro-mujer	0.002	0.008	13.995	0.002	0.364	47.629	173	538	0.017	0.082	0.6	0.046	0.034	42.2	0.186	0.322	0	0.302	134	20.3	0.612
W-Bogota	0.021	0.022	0.866	0.006	0.248	79.032	210	479	0.058	0.142	2.9	0.035	0.01	0.41	0.128	0.438	0.414	0.348	327	2.4	0.252
W-Bucaramanga	0.008	0.012	1.008	0.002	0.241	510.437	296	629	0.067	0.143	2.9	0.039	0.011	0.449	0.114	0.471	0.509	0.388	218	2.2	0.249
W-Cali	0.012	0.014	2.576	0.002	0.126	57.969	260	497	0.047	0.144	1.7	0.184	0.071	0.346	0.07	0.524	0.3	0.311	468	2.6	0.356
W-Medellin	0.024	0.015	0.929	0.006	0.196	55.545	187	451	0.047	0.123	1.6	0.098	0.037	0.383	0.115	0.415	0.433	0.298	283	3.4	0.378
W-Popayan	0.01	0.006	1	0	0.115	274.482	354	724	0.03	0.16	0.6	0.247	0.16	0.433	0.062	0.489	0.78	0.038	233	5.5	0.629

Table 2. Values of the 21 ratios in 30 Latin American MFIs

Inputs	Outputs
A. Credit officers (number)	1. Interest and fee income ($ thousands)
B. Operating expenses ($ thousands)	2. Gross loan portfolio ($ thousands)
	3. Number of loans outstanding (number)

Table 3. Inputs and outputs included in the DEA model, together with their units of measurement.

DMU	Input A Credit officers	Input B Operating expenses	Output 1 Interest and fee income	Output 2 Gross loan portfolio	Output 3 Number of loans outstanding
Adopem	92	1,483.273	3,341	7,597	39,717
Andes	195	9,098.855	16,238	70,058	52,954
Bancosol	173	10,816.344	18,082	82,984	41,317
Calpia	130	9,190.205	12,038	52,550	46,856
C-Arequipa	211	10,017.945	26,015	78,985	85,929
Cr-Arequipa	67	1,157.664	2,045	5,035	7,053
C-Cusco	66	3,910.601	10,020	34,954	28,506
C-Ica	78	2,322.093	4,470	14,102	18,534
Compartamos	525	17,726.376	40,115	48,605	166,580
Confia	82	3,667.626	8,042	18,723	24,320
Confianza	23	1,201.438	2,217	5,890	7,233
C-Sullana	223	5,293.925	11,300	31,843	56,343
C-Tacna	111	3,012.012	6,191	18,464	21,327
Cr-Tacna	27	818.522	1,366	3,892	4,756
C-Trujillo	347	8,436.381	16,838	59,047	81,571
Diaconia-Frif	38	957.577	1,908	7,206	15,495
D-Miro	20	751.709	1,099	2,607	8,415
Edyficar	92	5,254.613	8,862	24,216	25,201
Fie	114	3,955.857	7,967	36,317	28,910
Finamerica	72	3,040.092	4,555	15,414	20,287
Fincomun	82	5,113.527	4,754	6,317	11,027
Findesa	23	2,627.744	5,371	12,894	11,243
Nieborowski	40	896.714	2,792	6,449	9,619
Proempresa	25	1,680.174	2,931	6,491	8,031
Pro-Mujer	65	1,676.766	1,762	4,682	34,973
W-Bogota	39	1,355.444	2,055	6,095	19,466
W-Bucaramanga	60	1,737.249	3,101	8,201	37,789
W-Cali	118	3,121.965	8,229	27,423	63,463
W-Medellin	39	922.768	1,792	4,971	17,979
W-Popayan	85	1,505.178	5,454	14,270	61,341

Table 4. List of MFIs and the value of inputs and outputs

DMU	A1	A12	A123	A13	A2	A23	A3	AB1	AB12	**AB123**	AB13	AB2	AB23	AB3	B1	B12	B123	B13	B2	B23	B3
Adopem	16	16	60	60	15	60	60	62	62	**66**	66	54	66	66	62	62	66	66	54	66	66
Andes	36	64	64	48	64	64	38	66	85	**85**	66	85	85	38	49	81	81	49	81	81	14
Bancosol	45	86	86	47	86	86	33	67	90	**90**	67	90	90	33	46	81	81	46	81	81	9
Calpia	40	72	73	60	72	73	50	55	75	**78**	60	75	78	50	36	60	60	36	60	60	13
C-Arequipa	53	67	76	71	67	76	56	97	97	**97**	97	87	88	56	72	83	83	72	83	83	21
Cr-Arequipa	13	13	18	18	13	18	15	49	49	**49**	49	46	46	15	49	49	49	49	46	46	15
C-Cusco	65	95	95	80	95	95	60	100	100	**100**	100	100	100	60	71	94	94	71	94	94	18
C-Ica	24	32	42	39	32	42	33	64	66	**66**	64	66	66	33	53	64	64	53	64	64	20
Compartamos	33	33	52	52	16	45	44	78	78	**78**	78	30	45	44	62	62	62	62	29	29	23
Confia	42	42	53	53	41	52	41	81	81	**81**	81	56	57	41	61	61	61	61	54	54	16
Confianza	41	46	57	55	46	57	44	70	70	**70**	70	55	60	44	51	52	52	51	52	52	15
C-Sullana	22	26	41	40	26	41	35	66	66	**66**	66	65	65	35	59	63	63	59	63	63	26
C-Tacna	24	30	35	33	30	35	27	66	67	**67**	66	66	66	27	57	65	65	57	65	65	17
Cr-Tacna	22	26	32	31	26	32	25	56	56	**56**	56	52	52	25	46	50	50	46	50	50	14
C-Trujillo	21	30	41	37	30	41	32	62	75	**75**	62	75	75	32	55	74	74	55	74	74	24
Diaconia-Frif	22	34	63	59	34	63	56	63	81	**81**	63	81	81	56	55	79	79	55	79	79	40
D-Miro	24	24	61	61	23	61	58	52	52	**61**	61	38	61	58	40	40	40	40	37	37	27
Edyficar	41	47	52	50	47	52	38	65	65	**65**	65	51	56	38	47	49	49	47	49	49	12
Fie	30	57	57	43	57	57	35	70	100	**100**	70	100	100	35	56	97	97	56	97	97	18
Finamerica	27	38	50	45	38	50	39	55	56	**56**	55	56	56	39	41	53	53	41	53	53	16
Fincomun	25	25	26	26	14	22	19	37	37	**37**	37	14	22	19	26	26	26	26	13	13	5
Findesa	100	100	100	100	100	100	68	100	100	**100**	100	100	100	68	56	56	56	56	52	52	11
Nieborowski	30	30	41	41	29	41	33	94	94	**94**	94	77	77	33	86	86	86	86	76	76	26
Proempresa	50	50	59	59	46	58	44	71	71	**72**	72	48	60	44	48	48	48	48	41	41	12
Pro-Mujer	12	13	74	74	13	74	74	33	33	**74**	74	30	74	74	29	29	51	51	29	51	51
W-Bogota	23	28	72	70	28	72	69	53	53	**72**	70	49	72	69	42	47	47	42	47	47	35
W-Bucaramanga	22	24	87	87	24	87	87	59	59	**87**	87	51	87	87	49	50	53	53	50	53	53
W-Cali	30	41	82	78	41	82	74	84	95	**95**	84	95	95	74	73	93	93	73	93	93	50
W-Medellin	20	23	65	65	23	65	64	60	60	**65**	65	58	65	64	54	57	57	54	57	57	48
W-Popayan	28	30	100	100	30	100	100	100	100	**100**	100	100	100	100	100	100	100	100	100	100	100

Table 5. The 30 MFIs Efficiency results under the 21 specifications. The column in bold is the specification containing all the inputs and all the outputs.

Model	*PC1*	*PC2*	*PC3*	*PC4*
AB123	0.946	-0.041	0.059	0.008
AB23	0.914	0.028	0.058	-0.316
AB12	0.883	-0.394	-0.038	0.136
AB2	0.879	-0.352	-0.064	-0.218
AB13	0.854	0.188	0.080	0.396
B123	0.843	-0.245	-0.415	-0.163
AB1	0.832	-0.216	-0.031	0.497
B12	0.823	-0.341	-0.407	-0.112
B23	0.818	-0.206	-0.377	-0.349
B2	0.811	-0.312	-0.361	-0.298
A23	0.796	0.387	0.413	-0.178
A123	0.788	0.395	0.426	-0.147
B13	0.738	0.134	-0.521	0.380
B1	0.736	-0.015	-0.515	0.416
A13	0.696	0.609	0.361	0.065
A2	0.621	-0.476	0.599	-0.116
AB3	0.578	0.800	0.117	-0.054
A3	0.584	0.793	0.129	-0.055
B3	0.376	0.775	-0.458	-0.080
A1	0.516	-0.323	0.697	0.345
A12	0.589	-0.490	0.626	-0.048

Table 6. DEA component loadings matrix.

Model	Directional cosines				F	Adj R2
	g_1	g_2	g_3	g_4		
A1	0.09 (16.30)**	-0.06 (-10.20)**	0.12 (22.01)**	0.06 (10.91)**	243.19	0.971
A12	0.14 (21.64)**	-0.11 (-18.00)**	0.15 (22.99)**	-0.01 (-1.76)	330.95	0.978
A123	0.17 (27.90)**	0.08 (13.98)**	0.09 (15.07)**	-0.03 (-5.21)**	307.00	0.977
A13	0.14 (36.79)**	0.12 (32.20)**	0.07 (19.09)**	0.01 (3.46)*	691.59	0.990
A2	0.15 (24.98)**	-0.11 (-19.15)**	0.14 (24.09)**	-0.03 (-4.68)**	398.28	0.982
A23	0.17 (33.34)**	0.08 (16.20)**	0.09 (17.30)**	-0.04 (-7.44)**	432.07	0.983
A3	0.12 (29.28)**	0.16 (39.71)**	0.03 (6.48)**	-0.01 (-2.74)	620.98	0.988
AB1	0.15 (36.18)**	-0.04 (-9.39)**	-0.01 (-1.34)	0.09 (21.61)**	466.47	0.987
AB12	0.17 (20.77)**	-0.08 (-9.26)**	-0.01 (-0.89)	0.03 (3.20)*	132.07	0.948
AB123	0.16 (14.91)**	-0.01 (-0.64)	0.01 (0.93)	0.00 (0.13)	55.93	0.883
AB13	0.13 (15.91)**	0.03 (3.50)*	0.01 (1.49)	0.06 (7.37)**	80.48	0.916
AB2	0.20 (19.11)**	-0.08 (-7.65)**	-0.01 (-1.39)	-0.05 (-4.74)**	112.06	0.939
AB23	0.17 (18.65)**	0.01 (0.58)	0.01 (1.18)	-0.06 (-6.46)**	97.85	0.930
AB3	0.12 (30.52)**	0.16 (42.22)**	0.02 (6.18)**	-0.01 (-2.87)**	690.00	0.990
B1	0.11 (26.07)**	0.00 (-0.54)	-0.08 (-18.24)**	0.06 (14.74)**	307.43	0.977
B12	0.16 (24.29)**	-0.07 (-10.05)**	-0.08 (-12.01)**	-0.02 (-3.32)*	211.64	0.967
B123	0.15 (23.79)**	-0.04 (-6.91)**	-0.08 (-11.73)**	-0.03 (-4.60)*	193.16	0.964
B13	0.11 (24.28)**	0.02 (4.40)*	-0.08 (-17.14)**	0.06 (12.50)**	264.74	0.973
B2	0.17 (25.69)**	-0.07 (-9.89)**	-0.08 (-11.44)**	-0.06 (-9.44)**	244.50	0.971
B23	0.17 (26.65)**	-0.04)** (-6.72)**	-0.08 (-12.28)**	-0.07 (-11.38)**	258.94	0.973
B3	0.08 (9.15)**	0.16 (18.89)**	-0.09 (-11.16)**	-0.02 (-1.95)	142.26	0.951

** Significant at the 0.01 level. * Significant at the 0.05 level

Table 7. Pro-Fit Analysis. Linear regression results

	PC 1 ratios	PC 2 ratios	PC 3 ratios	PC 4 ratios	PC 5 ratios	PC 6 ratios	PC 7 ratios	PC 8 ratios
PC 1 DEA	0.099	-0.528**	0.612**	-0.208	-0.014	0.216	0.232	0.003
PC 2 DEA	0.876**	0.125	-0.044	-0.292	-0.101	-0.103	-0.044	-0.035
PC 3 DEA	-0.205	0.215	-0.250	-0.357	-0.008	0.324	0.168	0.027
PC 4 DEA	0.057	0.507**	0.446**	0.359	-0.053	-0.004	0.087	0.344

** Significant at the 0.01 level (bilateral)

Table 8. Pearson correlation coefficients between PC from ratios and PC from DEA

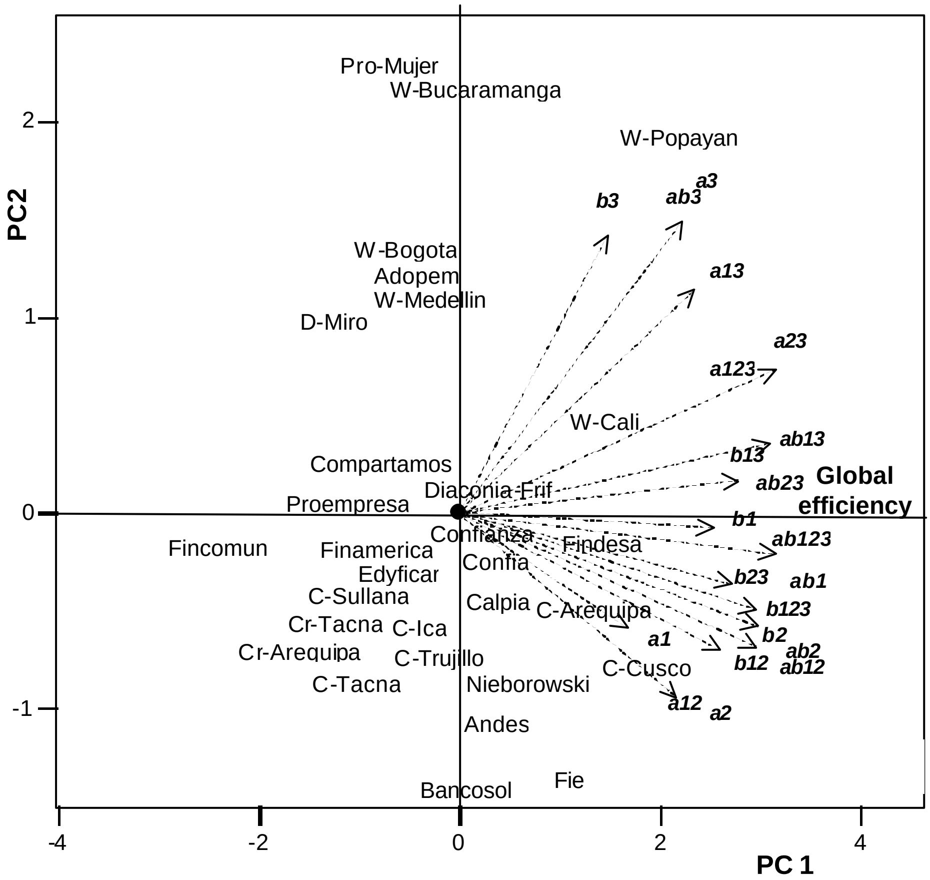

Figure 1. PC1 versus PC2. Profit lines.

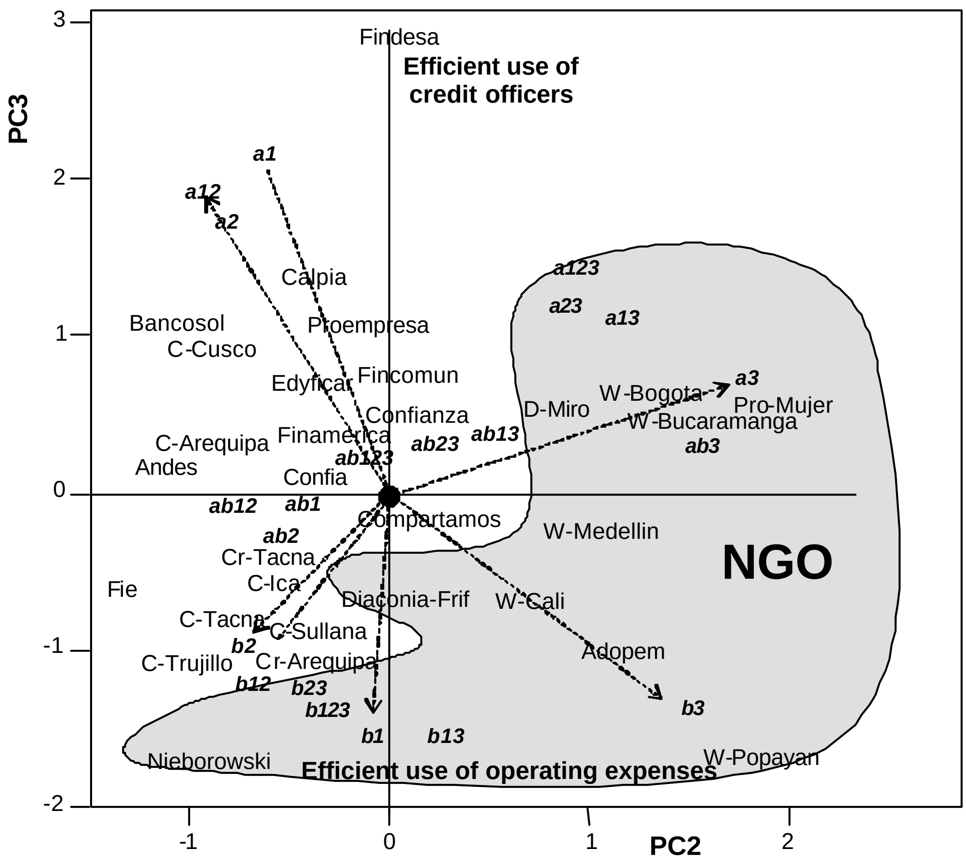

Figure 2. PC2 versus PC3. Profit lines. NGOs are shadowed

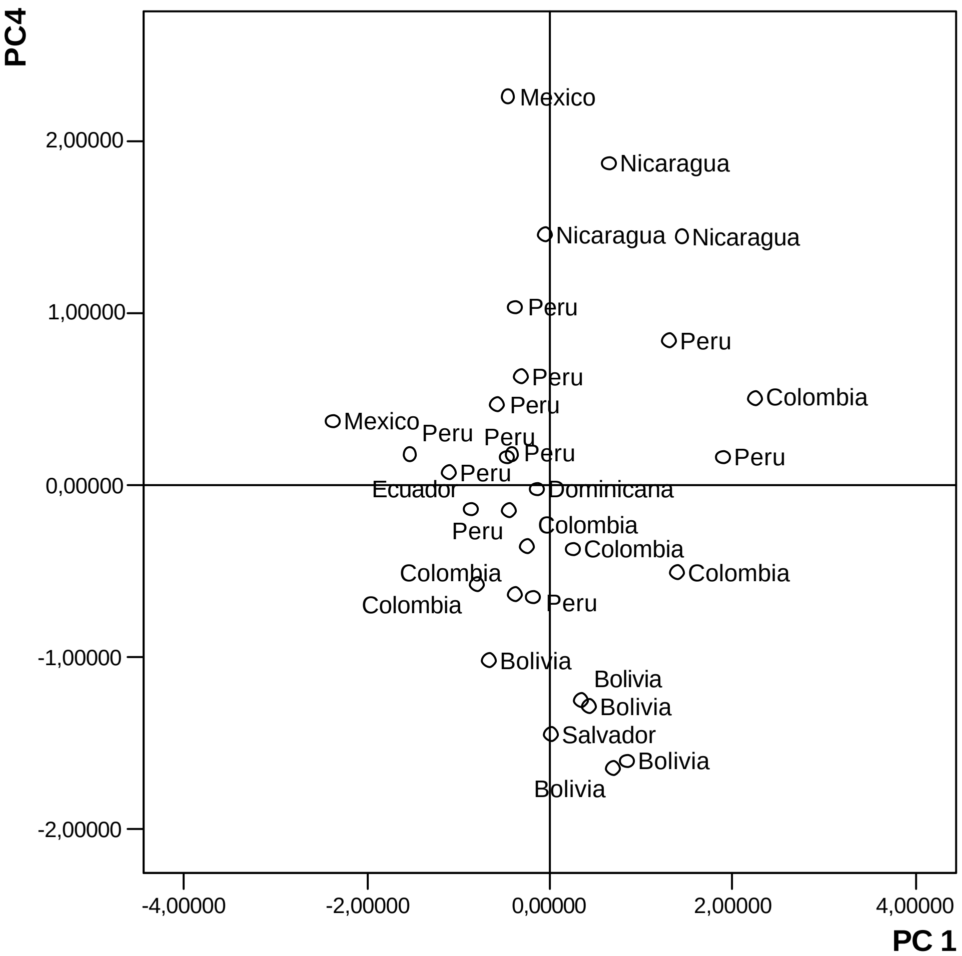

Figure 3. PC 1 versus PC 4. Country effect

Notes

[1] Some of the data had to be deduced from the Microrate source as follows:

A: Credit officers
Credit officers=Number of clients outstanding/Number of clients per credit officer

B: Operating expense
Operating expense= (Total operating expense/average gross portfolio)*average gross portfolio
To obtain the average gross portfolio, we take the gross portfolio data from adjusted comparison table 2002 and 2003.

Outputs data was directly taken from the adjusted comparison table