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Social efficiency in Microfinance Institutions*

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Social efficiency in Microfinance Institutions

Abstract

Microfinance Institutions (MFIs) are a special case in the financial world. They have a double financial and social role and need to be efficient at both. In this paper we try to measure the efficiency of MFIs in relation to financial and social outputs using Data Envelopment Analysis. For the analysis of financial efficiency we rely on existing literature for traditional financial institutions. To this we have added two indicators of social performance: impact on women, and a poverty reach index. A series of hypotheses on MFIs have been entertained, that concern the relationship between social and financial efficiency, and the relationship between efficiency and other indicators, such as profitability. Other aspects studied are the relation between social efficiency and type of institution -Non-Governmental Organisation (NGO), non-NGO-, and the importance of geographical region of activity. The results reveal the importance of social efficiency assessment.

JEL Classification: G290

Keywords: Microfinance Institutions (MFIs), Social Efficiency, Financial Efficiency, Data envelopment analysis (DEA), Microcredit.

1. Introduction

The 430 Microfinance Institutions (MFIs) listed in Mixmarket, a specialiced MFIs database, have an aggregated Gross Loan Portfolio of 5,618 \$ millions. This does not seem to be very much when compared to some of the large commercial banks. For example, the equivalent figure for JPMorgan Chase is 225,170 \$ millions. But the social task performed by MFIs has no equivalent in commercial banks. MFIs lend small amounts of money -microcredits- to individuals in a condition of social exclusion who have no recourse to traditional sources of finance. The average loan placed by the 430 MFIs mentioned to their approximately 18 million borrowers is about 300 \$. Microfinance Institutions (MFIs) have mushroomed around the world, particularly in developing countries. This makes it necessary to assess their performance, something that requires developing specially tailored tools. This paper represents an attempt to build a methodology to assess the performance of MFIs.

MFIs have much in common with traditional banks and other banking institutions. They collect deposits, grant loans and, in due time, collect debts with interest. Even though microcredits are, in general, not backed with any collateral, repayment rates are quite high, challenging the assumption that poor people do not pay.

But we should not forget the differences between traditional banks and MFIs. MFIs have a social face and their source of income is not only deposits, but also donations. Donors do not only value the financial aspects of the MFIs but also, and especially, their social aspects. Given this dual orientation of MFIs –financial and social the assessment of their performance is based on the so-called Double Bottom Line: financial (First Bottom Line) and social (Second Bottom Line). To date, no universal standard has emerged that can be used to measure the second bottom line; see Zeller et al. (2002).

The assessment of MFIs has traditionally been made under the Yaron (1994) framework of sustainability and outreach. Outreach or impact evaluates social performance, while sustainability focuses on financial performance; examples of the use of this methodology are Navajas et al. (2000), and Dunford (2000). This literature is

surveyed by Morduch (1999a). There is a debate between those who emphasise MFIs' financial aspects, and those who emphasise their social aspects. These two groups are known as institutionists and welfarists; Conning (1999), Woller et al. (1999). Institutionists are concerned with financial self-sufficiency and sustainability, and appear to be having the upper hand. These argue that sustainability is the most important goal of a MFI since a sustainable MFI will survive with its own revenues, without the help of external donors; Adams and Von Pischke (1992). Others say that MFIs have to help the poor first; and that sustainability should be a secondary issue; Hulme and Mosley (1996). Some enthusiastically support the win-win proposition. For this last group, MFIs that implement good banking practices will also alleviate poverty; but this proposition fails to receive good empirical evidence; Morduch (2000).

Another aspect in the assessment of financial efficiencies that has received much attention in recent times is efficiency. This has been extensively studied in the context of traditional banks. Data Envelopment Analysis (DEA) is normally used for the study of efficiency; Charnes et al. (1978), Charnes et al. (1990), Thanassoulis (2001). Examples of the use of DEA in banking are Sherman and Gold (1985), Berg et al. (1993), Berger and Mester (1997), Berger and Humphrey (1997), Athanassoupoulos (1997), Seiford and Zhu (1999), Soteriou and Zenios (1999), Kao and Liu (2004), and Casu et al. (2004). In this paper we extend the use of DEA to MFI performance assessment. We will, in particular, extend a previous ly published DEA model designed to assess MFI efficiency so that it can deal with both social and financial performance; Gutiérrez-Nieto et al. (2006).

The next section of this paper studies the assessment of MFIs taking into account both their social and financial aspects. This is followed by an empirical section in which a DEA model is introduced and estimated. A series of hypotheses pertaining to MFIs are discussed next. The paper ends with a concluding section.

2. Microfinance institutions (MFIs) and their assessment

The performance of MFIs is seldom assessed, and when this has been done, financial aspects have been given lip service; Morduch (1999a). This could, in part be due to the data available. The absence of reliable data is widespread in the case of MFIs –although some attempts have been made at ranking them- and when data is available, it is often not standardised. This contrasts with the excellent information available in the case of traditional financial institutions. This is sad because a higher level of transparency would result in better mechanisms for funds allocation, to the benefit of donors and investors; Tucker (2001).

In order to address the problem of lack of relevant information, a consortium of 28 public and private development agencies agreed on a set of guidelines on definitions of financial terms, ratios and adjustments for microfinance; see Consultative Group to Assist the Poorest- CGAP- (2003). The set of performance indicators is structured around four groups of financial ratios measuring sustainability and profitability, assets and liability management, portfolio quality, and efficiency and productivity. This last group of ratios attempts to reflect "how efficiently an MFI is using its resources, particularly its assets and personnel" (CGAP, 2003). Efficiency and productivity performance measures usually compare a cost measure with the loan portfolio or the number of clients.

In practice, the financial assessment of MFIs is carried out by conventional rating agencies and by rating firms that specialise in microfinances. However, the first group lacks experience in the MFI field, and the second group is not well established amongst investors. Firms that specialise in rating MFIs are beginning to adopt the vocabulary of traditional firms, or have searched to be franchised by them. MFI financial assessment takes place in two different forms: credit rating, mainly applied to microcredit bonds, and global risk assessment, where risk relates to the whole institution.

The most important rating methodologies to assess MFIs are CAMEL, GIRAFE, M-Cril, Microfinanza, Microrate, MICROS and MIRACLES. Most rating agencies adapt Standard and Poor's methods and concentrate on financial aspects, leaving aside their social function. CAMEL, GIRAFE, M-Cril, Microrate and Pacific have developed their own rating scales. The GIRAFE and MICROS methodologies assess sustainability. GIRAFE pays particular attention to efficiency.

Tools for the assessment of social impact are currently being developed by conventional financial institutions under the Global Reporting Initiative (GRI). GRI has taken upon itself the initiative of issuing sustainability reporting guidelines for the drafting of reports containing social and environmental indicators. A framework of Social Performance Indicators already exists with specific guidelines on how to calculate them; SPI (2003).

Name	Description	Analysis
IMP-ACT	International action-research programme that aims at improving the quality of microfinancial services and their impact on fighting poverty.	It relies on the collection of quantitative and qualitative information from MFI clients. Descriptive statistics, test of differences in means and medians, correlations and hypotheses tests are generated from data obtained.
AIMS	Assessing the Impact of Microenterprise Services (AIMS) tries to measure how microfinance interacts with their borrowers´ lives.	It places families at the centre of its analysis. It uses qualitative and quantitative techniques. It considers hypothesis at household, individual, enterprise and community levels.
SROI	Social Return On Investment (SROI) attempts to measure in the form of an investment ratio the social and environmental value created by an organisation.	The methodology is still under construction. For example, the income generated by enterprise tries to be measured through savings to donors.
ACCION PAF	Accion Poverty Assessment Framework (PAF) has been created by Accion, a not- for-profit North American organisation that groups MFIs, many of which are in Latin- America. It compares socio-economic characteristics of its clients against national and international poverty lines (example: a \$ a day).	The data it employs at the moment is the data available within the MFI. Income or expenditure is compared with poverty lines. It analyses correlations and multivariate regressions to assess the potential of some variables as proxies of poverty level. For example, loan size.
PAT	The Poverty Assessment Tool of CGAP (PAT) measures poverty outreach by placing the clients of a MFI in the context of the non-clients. This is the same methodology used by United Nations Human Development Index (HDI).	The analysis is done on the basis of 300 poverty indicators that are reduced to 30 by means of Principal Components Analysis. A poverty index is finally constructed from these indicators.
SPI	The Social Performance Indicators Initiative (SPI) goes beyond poverty outreach. Social performance would have four dimensions: Outreach to the poor and excluded, adaptation of the services and products to the target clients, improving social and political capital of clients and communities, and social responsibility of MFIs.	Four dimensions are collected by a questionnaire. The answers receive a weighting system from a principal components analysis. The results are represented by means of a rhombus, whose four vertices give a measure of MFI social performance.

Table 1. MFI social assessment methodologies.

As far as MFIs are concerned, the standard way of focusing into their social performance is through the measures of outreach in Yaron's framework. The methodological issues involved have been surveyed by Hulme (2000) who identifies three different paradigms: the scientific method, the humanistic tradition, and participatory action learning (PLA). Six methodologies used to assess outreach the social bottom line- deserve further discussion: IMP-ACT, AIMS, SROI, Accion PAF, CGAP (PAT) and SPI. These are described in outline in Table 1.

3. Empirical study

3.1 Sample and data

In this section we describe an empirical study whose aim is to calculate social efficiency in the context of MFIs, and to relate it with financial efficiency and with other indicators.

The data source is the Microfinance Information eXchange (MIX). According to its web page (Mixmarket.org), "The MIX intends to address one of the key challenges of the microfinance industry: the lack of reliable, comparable and publicly available information on the financial strength and performance of Microfinance Institutions, which underpins the development of the market for microfinance services". MIX publishes data that has been standardised across the industry, so as to make comparisons and benchmarking possible. The financial information published includes balance sheet accounts, and profit and loss accounts. For each MFI it also publishes social information on outreach and impact. The data used in this study has been obtained from the MIX webpage for 89 MFIs for which complete information was available. The total number of MFIs in the MIX database is 450. All the data corresponds to the year 2003. This was the most recent information available at the time of the study.

The data on which the study is based can be seen in Table 2. In the next subsection we discuss input and output selection for the DEA model and describe the logic for their selection and their calculation.

Name	Input A (Total	Input C (Operating	Input E (Number of	Output W (Number	Output P (Estimated	Output L (Gross loan	Output R (Financial
	assets , in US\$)	cost, in US\$)	èmployees)	of women borrowers)	number of	portfolio, in US\$)	revenue, in US\$)
2cm	2,098,432	185,817	23	2,414	2,913	1,400,438	124,476
adim	453,931	131,445	20	1,067	1,263	407,798	182,862
afk	1,777,969	206,967	8	35	154	1,706,577	421,057
al-ama	30.891.338	4.460.298	421	61.982	96.940	28.677.666	7.864.719
amssf	1.398.238	361,246	48	5.922	6.748	1.040.756	548.384
arenak	6 838 049	815 587	92	14 377	13 424	3 987 011	1 800 641
besa	14,800,554	1.780.563	59	850	2.844	15,114,430	3,423,294
hnr-a	1 151 171	84 976	29	1 746	3 635	876 130	225 090
bpr-b	339 901	49 443	17	1 299	1 720	237 946	76 849
card	11 660 255	1 953 210	446	74 182	73 420	6 141 755	2 672 123
chdiha	459 351	185 755	41	2 503	2 762	242 465	59 554
000100	7 953 192	676 554	55	2,000	4 781	4 582 302	1 004 626
cca	1 202 102	222 200	24	4 252	9.496	4,302,302	261 260
coop	5 062 015	322,333	100	4,200	20 601	5 261 057	1 172 200
corudob	75 199 604	11 169 664	103 644	16 070	100,00	3/ 272 000	15 562 020
ommb	10,100,094 E1 77E	15 010	041	10,970	1,044	54,013,220 FC 0C1	17.002,932
	04,115 2 226 EOE	13,213	3	00 540	001 7 507	1 855 710	0/0,000 0/6 0/1
COAC	2,220,393	237,143	19	10 107	17,537	1,000,710	240,041
constanta	4,764,453	1,000,970	207	13,197	17,000	3,536,047	1,950,236
coopec	43,772	7,639	4	12	0	29,821	6,814
crystar	661,600	167,262	23	/54	939	421,403	199,521
abaca	11,909,978	512,678	253	8,548	19,069	3,876,526	917,468
eclot	286,899	69,487	/	1,350	891	407,227	91,720
emt	7,692,748	1,428,926	208	70,051	88,187	5,765,281	1,687,881
esed	15,294,519	856,259	378	13,764	18,949	6,834,742	1,900,497
eshet	/82,874	/9,450	43	1,969	5,258	462,569	109,726
faulu	10,538,796	1,738,627	110	10,005	10,330	7,206,344	2,394,206
fdl	20,511,878	2,595,471	287	12,804	19,438	16,545,332	3,858,505
finance	751,254	304,889	31	5,584	6,469	434,298	111,181
fincat	2,752,181	1,383,505	142	27,444	26,110	1,854,834	1,501,637
finca-u	3,980,899	2,321,015	214	36,063	34,223	2,798,869	2,539,083
fjn	9,487,952	1,039,013	111	6,580	8,369	8,037,662	2,635,484
fmfb	21,492,095	1,124,288	123	0	2,933	1,188,896	793,471
fodem	1,121,330	3,280,022	27	2,398	2,189	939,824	320,259
fundacion	2,244,834	686,878	60	9,464	9,282	1,883,446	884,291
fundeser	1,723,550	395,308	41	2,294	4,624	1,373,113	421,003
gasha	1,097,506	137,136	69	3,494	5,294	413,742	102,548
ggls	399,371	419,083	27	2,197	2,215	137,957	105,143
gk	250,634	71,453	46	2,718	2,663	166,971	43,753
hope	637,538	168,553	31	1,106	1,415	603,488	183,338
iamd	105,622	24,049	7	2,711	2,766	56,550	29,662
idece	66,736	15,425	11	72	131	39,453	16,748
idf	2,846,745	317,232	302	36,580	35,220	2,626,382	579,149
imcec-d	1,386,479	154,686	26	1,462	2,685	688,449	177,910
imcec-t	907,359	171,761	16	451	1,002	571,122	163,644
issia	347,511	120,334	16	818	1,447	246,792	137,463
kafc	34,730,011	1,704,334	305	5,168	9,291	29,241,051	4,113,678
kashf	13,960,978	886,472	262	59,389	56,475	6,271,498	1,697,468
kpsca	225,444	53,644	10	286	663	128,063	82,873
krep	28,696,444	2,792,359	264	23,597	31,979	20,699,963	3,743,773
kscs	64,240	19,675	6	223	252	43,740	20,133

kvt	86,402	12,794	7	216	300	70,621	18,164
mec-a	70,367	8,690	4	149	171	69,248	17,841
mec-b	53,914	5,889	6	428	464	31,086	4,728
medf	185,471	70,224	29	1,125	1,163	136,257	50,644
meklit	299,875	31,721	19	2,057	2,876	252,232	59,947
metemamen	209,803	73,908	20	781	1,350	57,778	11,620
microfund	625,885	89,032	30	1,627	1,357	508,875	92,496
mikra	6,364,266	1,178,450	47	6,095	5,306	5,008,784	1,717,743
miselini	1,233,187	261,605	26	11,431	10,617	1,026,639	283,668
mmdct	177,484	35,066	10	306	372	131,447	43,270
mrfc	20,132,821	2,786,279	310	81	168	9,133,130	4,642,614
mushuc	6,020,514	219,591	20	2,057	5,504	5,418,325	1,006,835
nirdhan	6,641,263	379,855	196	27,457	24,442	3,016,171	846,407
ocssc	10,358,575	687,762	472	8,452	40,595	7,658,413	1,066,911
otiv-d	2,020,307	210,520	47	539	509	638,422	194,356
otiv-s	4,411,129	268,708	56	99	1,062	437,974	298,152
otiv-t	2,941,473	305,397	197	662	676	673,175	156,941
pca	8,835,958	1,505,113	206	31,109	52,941	6,885,926	2,543,291
peace	929,426	106,586	47	3,544	3,656	627,295	92,005
pedf	501,171	234,748	62	3,340	3,311	254,233	160,403
piyeli	1,493,827	296,468	33	2,989	3,707	1,206,656	335,354
pride	854,631	939,232	54	2,296	4,341	854,631	510,490
prizma	7,716,082	1,231,256	52	10,968	9,916	6,838,978	1,982,797
promujer	1,496,051	431,071	44	12,395	12,666	1,424,437	724,869
ptf	1,270,672	432,769	52	8,607	8,196	1,068,881	391,522
remecu	3,793,554	54,009	29	3,807	13,429	1,483,471	228,399
rusca	154,752	28,291	8	564	895	100,820	49,038
scscs	257,910	28,208	7	415	846	157,472	48,229
seawatch	87,819	50,084	12	1,800	2,000	35,557	1,082,432
sfpi	1,359,377	145,901	57	6,591	7,015	903,556	185,674
sidama	1,977,812	184,389	111	4,311	8,529	1,011,798	123,225
spbd	300,545	186,965	13	1,740	1,727	186,029	56,765
sunlink	1,191,404	418,246	28	1,955	3,163	1,056,823	415,672
tpc	2,882,718	594,452	162	28,501	30,059	2,267,148	683,387
tspi	7,500,759	1,988,886	466	74,634	75,060	5,383,755	2,830,017
wasasa	408,540	41,785	29	2,274	2,965	274,908	78,899
wisdom	2,485,619	277,016	103	4,062	8,083	1,404,463	283,549
xacbank	15,891,317	2,051,752	424	10,608	13,451	9,829,503	1,425,619
zakoura	15,005,820	3,050,681	472	115,411	117,675	12,444,768	4,448,042

Table 2. The 89 MFIs and values of inputs and outputs.

3.2 Output and input selection

Output and input selection is a key issue in the calculation of DEA efficiency. This study contemplates two aspects in efficiency calculation: social efficiency and financial efficiency. Financial efficiency calculation has a long pedigree in DEA applications, while very little has been published in the area of social efficiency assessment. Indeed, the number of studies that address the efficiency of financial institutions is very large. This tends to be associated with the estimation of production functions, either from the econometric (parametric) point of view, or from the DEA (non parametric) point of view. Some examples of efficiency studies in the financial institution area are Sherman and Gold (1985), Berger and Humphrey (1997), Berger et al. (2000), Almazan (2002), Berger and Mester (2003), Kao and Liu (2004) and Casu et al. (2004).

By far the most popular approach to modelling financial efficiencies is DEA. But within this approach, there is a debate between those researchers who see a financial institution as a production unit, and those who see it as an intermediation unit (Berger and Mester, 1997; Athanassoupoulos, 1997). Under the production approach, financial institutions are treated as firms that use physical inputs, employees, and expend money in order to obtain deposits, grant loans, and collect fees, much in the same way in which a factory would use capital, manpower, and raw materials in order to manufacture products to be sold (see Soteriou and Zenios, 1999). Under the intermediation approach, financial institutions aim at making a profit by being intermediaries in a series of financial transactions: they collect deposits and grant loans (Sealey and Lindley, 1977). In our opinion, the production model is best suited to MFIs, as the emphasis is in the granting of loans. In fact, many MFIs do not even collect deposits, a crucial aspect of the intermediation model, but receive donations and subsidies. As an example, Morduch (1999b) argues that the success of Grameen Bank is largely based on the subsidies received. This, of course, opens the debate of subsidies in the MFI world, but this is a debate into which we will not engage in this paper.

After a thorough review of the literature on DEA and financial institutions-Sherman and Gold (1985), Vassiloglou and Giokas (1999), Oral and Yolalan (1990), and Tulkens (1993), amongst others- we have settled for 3 inputs and 4 outputs. The three inputs are standard in the literature: assets (A), operating cost (C) and number of employees (E). Two of the outputs are financial- gross loan portfolio (L) and Revenue (R)-, and two outputs are social- the number of women borrowers (W) and an indicator that measures the extent to which the activities of the MFI institution can benefit the poorest (P). We will describe below how this indicator has been calculated. These social outputs have selected because MFIs claim to target women and the poor.

Table 3 summarises the inputs and outputs used, their definitions, and their units of measurement. Some of the data is measured in monetary units (dollars): assets (A), operating cost (C), gross loan portfolio (L) and financial revenue (R). The number of employees (E), and the number of women borrowers (W) are given in physical units.

Variable symbol	Variable Name	Definition	Unit
Input A	Total Assets	Total of all net asset accounts	(\$)
Input C	Operating Cost	Expenses related to operations, such as all personnel expenses, rent and utilities, transportation, office supplies, and depreciation	(\$)
Input E	Number of employees	The number of individuals who are actively employed by the MFI. This includes contract employees or advisors who dedicate the majority of their time to the MFI, even if they are not on the MFI's roster of employees	Number
Output W	Number of active women borrowers	Number of active borrowers who are female	Number
Output P	Indicator of benefit to the poorest	See text for formula and its rationale	Number
Output L	Gross loan portfolio	Outstanding principal balance of all of the MFI's outstanding loans including current, delinquent and restructured loans, but not loans that have been written off. It does not include interest receivable	(\$)
Output R	Financial revenue	Revenue generated from the gross loan portfolio and from investments plus other operating revenue	(\$)

Table 3. Inputs and outputs and their definitions

We will now proceed to discuss each input and output in detail.

Assets (Input A)

The value of assets has been included in financial efficiency models by, for example, Berger and Humphrey (1997), Berg et al. (1993), Seiford and Zhu (1999), and Luo (2003). Mixmarket defines assets as the "total of all net assets accounts". This value has been taken directly from the 31 December 2003 Mixmarket database.

Operating Cost (Input C)

Operating cost –or similar inputs- have been suggested by Athanassoupoulos (1997), Berger and Humphrey (1997), Pastor (1999) and Worthington (1998). Operating expense is defined by Mixmarket as "expenses related to operations, such as all personnel expenses, rent and utilities, transportation, office supplies, and depreciation".

Number of Employees (Input E)

The number of employees has been proposed as an input by Berg et al. (1993), Athanassoupoulos (1997), Berger and Humphrey (1997), Sherman and Gold (1985), Seiford and Zhu (1999), and Luo (2003) among others. In this study it contains: "the number of individuals who are actively employed by the MFI. This includes contract employees or advisors who dedicate the majority of their time to the MFI, even if they are not on the MFI's roster of employees".

Number of women borrowers (Output W)

Poverty is not solely an economic concept. Social conditions and the exercise of power are other aspects of poverty. This brings to the fore the issue of female empowerment. Thanks to microcredit, women can raise their status at home and within their society (Amin et al., 1994; Panjaitan-Drioadisuryo and Cloud, 1999). Microcredit empowers women by strengthening their economic roles and increasing their contribution to their families' support (Hashemi et al., 1996); so that they can play an active role in the development process (Goetz and Gupta, 1996). The number of women borrowers is measured by the number of active borrowers who are female, as given in the Mixmarket database and directly calculated from it.

Indicator of benefit to the poorest (Output P)

An important aim of microcredit is to fight against poverty. Karim and Osada (1998) think that the top-down policy of financing development is unlikely to impact on the poor, at least in the short term, and that it is much more effective to start at the bottom, by directly supporting the poor through microcredit. They argue that a microcredit policy is much more likely to bring about general welfare effects and economic growth than a policy that starts at the top. Matin et al. (2002) discuss how to design and provide the best financial services for the poor. They argue that microcredit

contributes to the fight against vulnerability and results on poverty reduction. The social impact of microcredit has been assessed, for example, by Copestake et al. (2001) in the case of Zambia, and by Mosley (2001) in Bolivia. The problem is how to measure poverty, and the extent to which microcredits are granted to the poor.

As a rough indicator of how far microcredit reaches the poor, MFIs employ the number of borrowers. Mixmarket's definition is: "The number of individuals who currently have an outstanding loan balance with the MFI or are responsible for repaying any portion of the Gross Loan Portfolio". The assumption is that an MFI that gives loans to many individuals is playing an important role in poverty reduction. But not all the borrowers need to be poor. Daley-Harris (2004) surveys 3000 MFIs, where 67.7% of their borrowers were among the poorest, although this percentage varies between institutions. Mixmarket defines as poor "clients below poverty line (where the poverty line is considered as population living on less than US\$2/day)". This is not totally satisfactory, as poverty is a relative concept and should be measured in relation to the general wealth of the population. For example, some microcredit institutions aim at reducing poverty in Europe, where the poverty threshold is clearly much higher. Besides, the number of "clients below poverty line" is often not available in the Mixmarket database.

Moreover, an institution that lends to many individuals may be lending only to the wealthier members of society. Wealthier members of society are, obviously, able to meet their loan repayments, and would qualify for larger loans than their poor counterparts, as financial institutions of all kinds are conservative with respect to risk. It follows that the "average loan balance per borrower" could be taken as a measure of the commitment that an MFI has in poverty reduction. This is an indicator also published by Mixmarket and contained in its database. The smaller the average balance of the loan, the deeper the reach of the microcredit.

We are not satisfied with "average loan balance per borrower" as an indicator of outreach in poverty reduction, because it is measured in monetary units, and the same amount of money may mean different things in different countries depending on the average per capita income. We agree with Morduch (2000) when he writes "by far, loan size has been the predominant metric for comparison of outreach. But loan size is a rough and indirect measure". We prefer to think in relative terms. To do this, we have

divided the "average loan balance per borrower" by the per capita Gross National Income (pcGNI).

$$K = \frac{\text{Average loan balance per borrower}}{\text{pcGNI}}$$
(1)

The higher the value of K, the larger is the average loan in relative terms.

To illustrate the previous procedure, consider the following example. Both Cerudeb and Finca-U operate in Uganda, a country whose per capita GNI is 240\$. Cerudeb made lent to 44,796 borrowers while Finca-U lent to 36,912 borrowers. The average loan per borrower is 778\$ in the case of Cerudeb and 76\$ in the case of Finca-U. In relative terms, 778 is 3.24 times the value of per capita GNI in Uganda, while the equivalent figure for 78 is 0.32 times.

Having calculated the value of K for every MFI and every country, we standardise them value to the 0,1 range by removing the minimum value of K and dividing by the range of K. In this way we obtain a value between 0 and 1 where a value near 0 indicates that the institution lends to the poorest. However, we prefer to have a value near one associated with achieving the objective of reaching the poor. To this effect, we deduct the previously calculated number from one. In this way we calculate p.

$$p_i = 1 - \frac{K_i - Min(K)}{Range(K)}$$
(2)

We would like to see MFIs to make a large number of loans, associated with high values of p. For every MFI, we multiply p by the number of active borrowers in order to construct an indicator that takes into account both aspects. In this way we calculate the output P. The value of P for every MFI can be seen in Table 2. The value of P for Cerudeb is 7,344 and the value of P for Finca-U is 34,223. From the point of view of fighting poverty, Finca-U appears to be more committed than Cerudeb.

We now turn our attention to financial outputs:

Gross loan portfolio (Output L)

Gross loan portfolio or similar measures are often mentioned in the literature: Berger and Humphrey (1997), Berg et al. (1993), Sherman and Gold (1985), Worthington (1998), Athanassoupoulos (1997), English et al. (1993), Miller and Noulas (1996), and Wheelock and Wilson (1999). Mixmarket defines it as: "the outstanding principal balance of all of the MFI's outstanding loans including current, delinquent and restructured loans, but not loans that have been written off. It does not include interest receivable".

Financial Revenue (Output R)

Financial revenue is used by Miller and Noulas (1996), Pastor (1999), and Seiford and Zhu (1999). Mixmarket defines financial revenue as "revenue generated from the gross loan portfolio and from investments plus other operating revenue".

3.3 Specifications and DEA efficiencies

Berger and Humphrey (1997) suggest that, in order to assess efficiency in financial institutions, a variety of specifications should be entertained, and the results should be compared. In this case we mean by specification, a particular combination of inputs and outputs in the DEA model. In order to simplify the discussion of the different specifications we have introduced a mnemotechnic notation. The first part of the notation contains the inputs, and the second part contains the outputs. In this way, ACE-W is a specification that includes the three inputs (Assets, Costs, and Employees) and one output (Women). Each specification is consistent with a different way of measuring efficiency. ACE-WP would measure social efficiency, as only social outputs are included. ACE-P would be an alternative social specification that would only take into account the impact that the MFI has on the fight against poverty. From another perspective, ACE-LR, would attempt to measure only financial efficiency. DEA models also incorporate financial and other ratios. For example, C-R is just an efficiency ratio that is obtained dividing Revenues by Operating Cost.

DEA efficiencies were calculated for each MFI using the CCR model of constant returns to scale; (Charnes, Cooper, and Rhodes, 1978). The specifications entertained were: ACE-WP, ACE-W, ACE-P, ACE-LR, ACE-L, ACE-R, and C-R. DEA efficiency scores for each MFI under each specification can be seen in Table 4.

	S	Social efficiency			Financial e	fficiency	
	ACE-WP	ACE-W	ACE-P	ACE-LR	ACE-L	ACE-R	C-R
2cm	29.87	24.75	28.36	64.70	64.70	6.00	3.10
adim	15.59	13.35	15.59	64.46	63.29	10.14	6.44
afk	4.14	1.00	4.14	87.66	93.94	58.35	9.41
al-ama	52.85	33.49	52.43	79.94	79.76	20.71	8.16
amssf	34.11	30.09	33.99	53.75	52.44	12.67	7.02
aregak	36.33	36.33	33.20	54.53	52.57	21.70	10.22
besa	10.44	3.28	10.41	92.15	100.00	64.32	8.90
bpr-a	32.01	18.19	32.01	77.26	76.55	12.26	12.26
bpr-b	28.97	23.26	28.97	60.58	59.57	7.19	7.19
card	42.14	42.14	40.51	44.22	42.79	6.64	6.33
cbdiba	22.96	21.23	22.96	37.25	37.19	1.61	1.48
cca	19.34	9.12	18.77	56.51	57.22	20.25	6.87
ссср	82.00	40.30	82.00	46.39	50.20	12.07	3.75
сер	92.62	76.14	90.87	91.40	90.99	14.19	14.19
cerudeb	6.02	6.02	2.50	40.26	41.79	26.92	6.28
cmmb	13.19	7.47	13.19	73.71	73.27	6.28	5.17
coac	86.73	6.57	86.73	77.40	79.04	14.36	4.80
constanta	21.03	15.93	21.03	53.48	52.07	10.44	5.34
coopec	1.39	1.39	0.11	54.67	54.57	4.13	4.13
crystal	9.88	8.01	9.88	45.80	44.87	9.62	5.52
dbacd	24.27	14.69	24.27	35.78	35.51	8.28	8.28
eclof	44.93	44.93	29.90	100.00	100.00	14.53	6.11
emt	100.00	81.27	100.00	59.36	58.69	9.00	5.47
esed	15.54	14.19	15.54	47.70	47.08	10.27	10.27
eshet	52.48	21.79	52.48	55.82	55.53	6.39	6.39
faulu	22.63	20.69	20.94	56.84	59.61	24.13	6.37
fdl	15.59	10.34	15.45	71.83	71.55	14.90	6.88
finance	51.25	44.80	51.25	40.83	40.73	3.98	1.69
fincat	49.02	49.02	45.87	49.78	47.48	11.72	5.02
finca-u	42.88	42.88	40.00	52.33	49.53	13.15	5.06
fjn	17.66	13.65	16.97	79.59	78.12	26.32	11.74
fmfb	5.15	0.00	5.15	6.58	5.89	7.15	3.27
fodem	20.65	20.65	19.04	59.61	59.31	13.15	0.45
fundacion	38.07	37.25	36.47	60.31	59.11	16.34	5.96
fundeser	26.47	12.99	26.47	58.16	57.44	11.38	4.93
gasha	31.55	22.44	31.55	33.77	33.56	3.46	3.46
ggls	21.43	21.43	21.18	25.42	24.34	4.32	1.16
gk	42.25	42.25	40.57	47.08	46.93	2.83	2.83
hope	11.34	9.01	11.34	67.12	66.69	6.56	5.03
iamd	100.00	100.00	100.00	40.48	38.72	5.71	5.71
idece	7.52	4.20	7.52	43.78	42.49	5.02	5.02
idf	100.00	100.00	89.30	84.91	84.70	8.45	8.45
imcec-d	23.99	13.81	23.99	45.94	45.57	7.59	5.32

imcec-t	14.49	6.42	14.49	49.46	49.54	11.34	4.41
issia	22.39	12.85	22.39	51.41	50.03	9.52	5.29
kafc	6.88	4.19	6.68	90.36	90.36	14.95	11.17
kashf	59.42	59.42	51.37	46.94	46.40	8.86	8.86
kpsca	16.37	7.16	16.37	42.90	40.33	9.19	7.15
krep	28.17	20.33	26.69	68.47	68.73	15.72	6.20
kscs	15.00	13.53	15.00	48.90	47.97	4.73	4.73
kvt	19.57	14.84	19.57	69.64	69.16	6.57	6.57
mec-a	16.07	15.13	16.07	88.57	87.89	9.50	9.50
mec-b	65.28	63.06	63.13	53.21	53.21	3.71	3.71
medf	23.94	23.63	23.94	52.39	51.76	3.34	3.34
meklit	72.35	56.91	72.35	78.65	78.25	8.74	8.74
metemamen	24.57	14.49	24.57	19.40	19.40	0.73	0.73
microfund	16.19	16.19	12.67	69.67	69.67	4.81	4.81
mikra	29.50	29.50	24.38	62.88	72.37	40.52	6.74
miselini	100.00	100.00	95.34	62.48	62.09	12.10	5.02
mmdct	9.36	7.89	9.36	57.62	56.68	5.71	5.71
mrfc	0.12	0.06	0.12	40.97	39.20	16.60	7.71
mushuc	60.33	23.39	59.42	100.00	100.00	55.81	21.21
nirdhan	63.62	63.62	45.44	48.34	47.69	10.31	10.31
ocssc	43.19	10.75	43.19	75.79	75.79	7.18	7.18
otiv-d	2.90	2.90	2.59	29.96	29.51	4.58	4.27
otiv-s	4.30	0.45	4.30	11.09	10.32	5.90	5.13
otiv-t	1.92	1.90	1.76	21.49	21.39	2.38	2.38
pca	60.27	36.14	60.27	64.42	62.95	13.69	7.82
peace	29.52	29.35	27.70	61.50	61.50	3.99	3.99
pedf	25.96	25.96	25.23	36.94	35.74	3.16	3.16
piyeli	26.51	21.01	26.28	62.26	61.71	11.27	5.23
pride	20.29	10.95	20.29	72.63	70.45	10.48	2.51
prizma	47.97	47.97	41.18	74.05	82.46	42.27	7.45
promujer	70.67	67.41	68.53	68.66	67.08	18.26	7.78
ptf	41.13	41.13	38.68	59.96	59.26	8.35	4.19
remecu	100.00	62.00	100.00	100.00	100.00	19.57	19.57
rusca	28.07	18.15	28.07	53.41	51.32	8.02	8.02
scscs	29.35	15.12	29.35	57.20	56.32	7.91	7.91
seawatch	86.96	79.86	86.96	100.00	28.53	100.00	100.00
sfpi	40.44	39.93	38.46	61.63	61.61	5.89	5.89
sidama	36.17	20.52	36.17	49.04	49.04	3.09	3.09
spbd	33.44	33.44	32.74	43.90	43.61	4.84	1.40
sunlink	26.50	16.17	26.50	63.36	63.27	16.46	4.60
tpc	46.63	45.21	46.63	59.92	59.20	5.32	5.32
tspi	41.18	41.18	40.62	51.83	50.57	6.73	6.58
wasasa	56.33	47.61	56.33	63.93	63.12	8.74	8.74
wisdom	23.47	12.97	23.47	51.87	51.87	4.74	4.74
xacbank	7.63	6.28	7.63	54.55	54.55	3.73	3.21
zakoura	61.54	61.54	59.77	64.08	62.77	10.45	10.45
Mean	35.53	28.17	34.21	58.37	57.42	13.08	7.31
St dev	26.29	24.00	25.60	19.12	19.44	14.80	10.50

 Table 4. Efficiencies DEA under the 7 models -. The last row shows the column mean and standard deviation.

Analysis of the results reproduced in Table 4 shows that average efficiency for the specification of the social model ACE-WP is 35.53%. Average efficiency for the financial specification ACE-LR is 58.37%. Average efficiency is particularly low under specification whose output is revenues ACE-R, and even lower under the specification C-R, with only 7.31%.

No MFI is 100% efficient under all 7 specifications. Take the case of the MFI Remecu. Remecu is 100% efficient under ACE-WP and ACE-LR, suggesting that it is efficient both socially and in financial terms. However, when we look at simplified models we find that under ACE-P is 100% efficient but only 62% under ACE-W, suggesting that Remecu is better at fighting poverty than at promoting women empowerment. Turning to simplifications in financial efficiency specifications, we can see that Remecu is 100% under ACE-L but only 19.57% under ACE-R. In other words, it is good at placing loans but not so good at obtaining revenues. We can summarise the analysis of Remecu, by saying that it is an efficient organisation whose efficiency relies on fighting poverty by placing loans, but that it could do better in supporting women and in generating revenues. We see that estimating a variety of specifications can help us to go behind the mere efficiency score to identify the strengths and weaknesses of an MFI. Other MFIs could be studied in the same way.

Some MFIs are financially 100% efficient but reach low scores for social efficiency. An example is Eclof whose financial efficiency is 100% with specification ACE-LR, but whose social efficiency drops to 44.93% when ACE-WP is estimated. The converse is also true, some MFIs achieve high social efficiency scores but low financial efficiency scores. An example of this last case is Iamd: 100% with ACE-WP but only 40.48% with ACE-LR.

A series of hypotheses will now be put forward about the relationship between financial and social efficiency scores. This will be the subject of the next section.

3.4 Hypotheses on social efficiency

H1: socially efficient MFIs are also financially efficient

It can be conjectured that in order to remain socially efficient, an MFI has to be financially efficient, since an MFI that makes many social contributions but is not financially viable cannot last long. The key to survival is self-sufficiency, and this implies financial efficiency as only self-sufficient entities can guarantee their survival. There may, of course, exist MFIs that are not financially efficient, provided generous donors support them.

Table 5 shows Pearson correlation coefficients between DEA social specifications, DEA financial specifications, and a set of standard banking efficiency ratios: C/I (Operating Cost/Net Operating Income), C/B (Operating Cost/Number of Active Borrowers), and C/L (Operating Cost/Gross Loan Portfolio). Levels of significance are also shown.

The correlation between social efficiency (ACE-WP) and financial efficiency (ACE-LR) is 0.346. This is significantly different from zero at the 1% level (two way test), but it is rather small. The correlation between efficiencies under specifications ACE-WP and C-R is even smaller, at 0.291. A higher value (-0.507) is obtained when the results of specification ACE-WP are correlated with cost per borrower (C/B). The sign is negative, indicating that the higher the cost of the loan, the least efficient is the MFI. Similar comments can be made if we look at the correlations between simplified versions of the social efficiency specification (ACE-W, and ACE-P), financial efficiency specifications, and performance ratios.

	ACE-WP	ACE-W	ACE-P	ACE-LR	ACE-L	ACE-R	C-R	CII	C/B	C/L
ACE-WP	1	0.891**	0.994**	0.346**	0.256*	0.135	0.291**	-0,052	-0,507**	-0,189
		(0.000)	(0.000)	(0.001)	(0.016)	(0.208)	(0.006)	(0,629)	(0,000)	(0,076)
ACE-W		1	0.865**	0.242*	0.140	0.097	0.274**	-0,053	-0,453**	-0,121
			(0.000)	(0.022)	(0.192)	(0.366)	(0.009)	(0,623)	(0,000)	(0,258)
ACE-P			1	0.337**	0.241*	0.132	0.299**	-0,046	-0,507**	-0,179
				(0.001)	(0.023)	(0.218)	(0.004)	(0,669)	(0,000)	(0,094)
ACE-LR				1	0.918**	0.527**	0.412**	-0,132	-0,216*	-0,543**
					(0.000)	(0.000)	(0.000)	(0,217)	(0,045)	(0,000)
ACE-L					1	0.328**	0.039	-0,093	-0,143	-0,526**
						(0.002)	(0.717)	(0,384)	(0,187)	(0,000)
ACE-R						1	0.728**	-0,103	0,280**	-0,235*
							(0.000)	(0,335	(0,009)	(0,027)

C-R				1	-0,103	-0,117	-0,213*
					(0,338	(0,279)	(0,045)
C/I					1,000	-0,030	0,020
						(0,782)	(0,849)
C/B						1,000	0,307**
							(0,004)
C/L							1,000

** Significant correlation at the 0,01 level (two-way).* Significant correlation at the 0,05 level (two-way).

 Table 5. Pearson correlations between efficiencies and efficiency ratios.

Returning to the correlation between efficiencies under specification ACE-WP and ACE-LR, the scatter plot turns out to be revealing. This is shown in Figure 1. The figure has been divided into four quadrants, each one of them revealing different MFI behaviour.



Figure 1. Social efficiency (ACE-WP) vs financial efficiency (ACE-LR)

The upper rigth hand corner of Figure 1 contains MFIs with relatively high financial and social efficiencies. Remecu, the MFI that appears in the extreme corner of the graph, is 100% efficient from both points of view. Other MFIs, such as CEP, IDF, and Seawatch achieve high values in both measures of efficiency. These MFIs could be described as "industry leaders".

A large group of MFIs, on the top left hand corner of Figure 1, are financially efficient but not socially efficient. While it is desirable that financial efficiency be maintained, these institutions could improve their social efficiency. Under the present model, such objective would be achieved by granting smaller loans to more individuals, particularly to women.

The lower left-hand side corner of Figure 1 groups MFIs with low values of social efficiency and low values of financial efficiency. They should reconsider their operations, or run the risk of not being able to survive.

Lastly, the fourth quadrant, on the bottom right-hand corner, contains MFIs that are socially efficient but financially inefficient. This quadrant is almost empty. IAMD is the only MFI that seats clearly in this quadrant. IAMD claims to lend only to customers that earn less than 1\$ a day.

Amongst the 89 MFIs in the study, only in 13 of them was social efficiency found to be higher than financial efficiency. The conclusion is that, when faced with a choice between financial efficiency and social efficiency, institutions would aim for financial performance in order to guarantee the possibility of being able to continue with their social work. We conclude that the evidence is consistent with hypothesis 1 that socially efficient MFIs are also financially efficient.

H2: Socially efficient MFIs are efficient in fighting poverty and supporting women

Microcredit schemes focusing on women have become a major feature of donor strategies to alleviate poverty, and funding is likely to further increase into the next century (Rankin, 2001). The microcredit literature shows that women are a good credit risk (Hulme and Mosley, 1996); and that their businesses have a better family members' impact than those run by men (Smith, 2002; Todd, 1996). But Hulme and Mosley (1996) argue that lending to women is much more complex than first thought, and the assumption that every loan given to a woman is used for her own activities has been challenged by Goetz and Gupta (1996), who find that significant proportions of female credit are in fact controlled by male relatives. However, Mahmud (2003) concludes that microcredit can possibly reduce male bias in welfare outcomes, particularly in poor households.

Some MFIs have as their specific objective to support poor women. The Daley-Harris (2004) survey of 3,000 MFIs, found that 55.9% of the borrowers were women. Out of the 89 MFIs in the sample, 12 lend solely to women. In general, 64% of all loans in our sample are made to women. It appears to the case that supporting women is seen as an effective way to combat poverty. We would expect that those institutions that are efficient at supporting the poor are also efficient at supporting women.

Overall social efficiency has been measured by means of the specification ACE-WP. We turn our attention to simplifications of this specification: ACE-W, and ACE-P and to the relationship between the results of the three specifications. We see in Table 5 that the correlations between efficiencies obtained by the three specifications are positive and very high. In particular, we see that Pearson correlation coefficient between efficiencies under ACE-W and ACE-P is 0.865. To further explore this correlation, the graph of efficiencies under ACE-W versus efficiencies under ACE-P has been reproduced in Figure 2.



Figure 2. Efficiency in supporting women (ACE-W) vs efficiency in supporting the poor (ACE-P)

We see that most MFIs plot along the diagonal in Figure 2 as would be expected from the high correlation coefficient. The exception is Coac, an efficient institution that makes many loans to the poor but only 7% of its loans support women.

This hypothesis is clearly supported by the data.

H3: NGOs are more socially efficient than non-NGO MFIs

MFIs exist under a variety of organisational structures: banks, non-bank financial institutions, cooperatives, credit unions, and non-governmental organisations

(NGOs). NGOs are not-for profit organisations often supported by volunteers. According to Dichter (1996), NGOs have a comparative advantage in their ability to reach the poor. They emphasise their social role over their financial performance, although, as mentioned in H1, they cannot neglect financial efficiency in the pursuit of sustainability. We could conjecture that, as a consequence of the emphasis that they put into social objectives, NGOs are more socially efficient than non-NGOs. We do not expect to find differences between NGOs and non-NGOs in terms of financial efficiency.

Amongst the 89 MFIs studied in this paper, 37 are non-governmental organisations (NGOs). Table 6 shows descriptive statistics for efficiencies under various specifications, both for NGOs and for non-NGOs. Some differences can be seen in Table 6, but in order to establish if the differences are significant, two different tests have been performed, ANOVA, and a non-parametric test of differences in means. It has been necessary to resort to non-parametrics because efficiencies are not normally distributed. The results are reproduced in Table 7.

		N	Average	Standard deviation	Min	Max
	non-NGO	52	32.286%	26.838%	0.12%	100%
ACE-WP	NGO	37	40.091%	25.153%	10.44%	100%
	Total	89	35.530%	26.291%	0.12%	100%
	non-NGO	52	22.084%	20.933%	0.00%	81.27%
ACE-W	NGO	37	36.713%	25.685%	3.28%	100%
	Total	89	28.166%	24.008%	0.00%	100%
	non-NGO	52	31.330%	26.594%	0.11%	100%
ACE-P	NGO	37	38.263%	23.897%	10.41%	100%
	Total	89	34.212%	25.599%	0.11%	100%
	non-NGO	52	57.999%	20.621%	6.58%	100%
ACE-LR	NGO	37	58.888%	17.038%	25.42%	100%
	Total	89	58.369%	19.115%	6.58%	100%
	non-NGO	52	56.838%	20.742%	5.89%	100%
ACE-L	NGO	37	58.229%	17.683%	24.34%	100%
	Total	89	57.416%	19.436%	5.89%	100%
	non-NGO	52	13.963%	17.285%	0.73%	100%
ACE-R	NGO	37	11.841%	10.458%	1.61%	64.32%
	Total	89	13.081%	14.799%	0.73%	100%
	non-NGO	52	8.359%	13.441%	0.73%	100%
C-R	NGO	37	5.826%	3.086%	0.45%	14.19%
	Total	89	7.306%	10.496%	0.45%	100%

Table 6. Descriptive statistics, NGO vs Non-NGO.

		ANOVA		Non parametric				
	Wilks's Lambda	F	Sig.	Mann- Whitney U	Wilcoxon, W	Ζ	Sig.	
ACE-WP	.978	1.925	0.169	742.000	2120.000	-1.832	0.067	
ACE-W	.909	8.732	0.004	577.000	1955.000	-3.205	0.001	
ACE-P	.982	1.596	0.210	746.000	2124.000	-1.798	0.072	
ACE-LR	.999	.046	0.830	958.500	2336.500	-0.029	0.977	
ACE-L	.999	.110	0.741	956.000	2334.000	-0.050	0.960	
ACE-R	.995	.441	0.508	886.500	2264.500	-0.629	0.530	
C-R	.986	1.263	0.264	874.500	1577.500	-0.728	0.466	

Table 7. ANOVA test for differences in means and non-parametric means test.NGO vs No NGO.

Table 6 shows that NGOs have higher average efficiency levels in all 3 models of social efficiency: ACE-WP, ACE-W and ACE-P. Turning to financial efficiency models, the results are mixed. NGOs achieve higher average efficiencies under models ACE-LR, and ACE-L, but lower average efficiencies under models ACE-R and C-R. We can see in Table 7 that, with the exception of ACE-W, such differences are not significant. The only field in which NGOs clearly outperform non-NGOs is the support of women.

We conclude that average efficiencies under the various models are in line with the hypothesis in the sense that average social efficiencies are higher for NGOs, although such differences are only significant in the case of women.

H4: There is a positive and significant relationship between profitability and social efficiency

Several authors have studied the relationship between profitability and efficiency in banking: Soteriou and Zenios (1999), Luo (2003), and Goddart et al. (2004). MFI and profitability appears to be a contradiction in terms, but out of the 89 MFIs in the sample, 58 have profits. The argument is that MFIs need to be profitable in order to be sustainable, and that a profitable organisation is so because it can identify opportunities for supporting profitable projects. The reverse view is that MFIs are not oriented towards profit maximisation, and that profits, while being important for sustainability, are not a yardstick against which the institution should be assessed.

Profitability can be measured in a variety of ways. Here we measure profitability by means of two standard ratios: return on assets (ROA) and return on equity (ROE).

We see in Table 8 that the correlation between social efficiency measures and profitability, although always positive, is also always low and never significantly different from zero at the 5% level. The two measures of profitability are highly correlated (0.768), as would be expected.

	ACE-WP	ACE-W	ACE-P	ROA	ROE	Age	Transparency
ACE-WP	1.000	0.891**	0.994**	0.116	0.206	0.068	0.060
		(0.000)	(0.000)	(0.279)	(0.053)	(0.526)	(0.574)
ACE-W		1.000	0.865**	0.093	0.151	0.167	0.062
			(0.000)	(0.386)	(0.159)	(0.118)	(0.565)
ACE-P			1.000	0.112	0.208	0.037	0.052
				(0.296)	(0.050)	(0.729)	(0.627)
ROA				1.000	0.768**	0.127	0.214*
					(0.000)	(0.234)	(0.044)
ROE					1.000	0.132	0.123
						(0.217)	(0.252)
Age						1.000	0.119
							(0.266)
Transparency							1.000
Transparency							1.00

** Significant correlation at the 0,01 level (two-way).

* Significant correlation at the 0,05 level (two-way).

Table 8. Pearson's correlation between social efficiency and other indicators.

Hypothesis H4 is rejected by the data: we have not found any significant relationship between profitability and social efficiency.

H5: There is a positive and significant relationship between the age of the MFI and social efficiency

Any human activity is subject to a learning process. As the MFI matures, one would expect it to become more efficient at achieving its social objectives. The

relationship between age and bank efficiency has been studied, among others, by Canhoto and Dermine (2003).

No relationship between efficiency and age is apparent in Table 8. The correlations between social efficiencies and age are low for all three DEA models. No correlations significantly different from 0 were found. We also calculated Pearson correlation coefficient between age and size, and the value obtained was 0.382, significantly different from zero. This means simply that older FMIs tend to be larger.

Hypothesis H5 is not supported by the data. MFIs do not become wiser as they grow older, they just get fatter.

H6: There is a positive and significant relationship between transparency and social efficiency

The subject of why firms disclose information has been long debated in the Accounting literature. Parsons (2003) surveys the usefulness to donors of the accounting information from non-profit organizations. A review of this literature suggests that firms that perform well are interested in revealing the details of their path to success. We can extend such reasoning to MFIs by putting forward the hypothesis that the most socially efficient institutions would also be the ones that are most transparent.

Mixmarket measures transparency by means of a "diamond" system. The number of diamonds increases as transparency increases. In order to get the full set of five diamonds, MFIs need to publish audited accounts, add external ratings, benchmarking studies, and other information.

We can see in Table 8 that the correlation between social efficiency and transparency is very low under all specifications, and not significantly different from zero. There is only one different from zero positive correlation. This is the correlation between return on assets and transparency (0.214). As the variable transparency is ordinal, we also calculated Spearman correlation coefficients. Results were very similar:

the value of the coefficient was 0.264. Both findings are very much in line with what would be expected from accounting research.

Perhaps the reason why we do not find any support for H6 is simply that social efficiency is a score derived from a DEA model, and that socially efficient MFIs are not fully aware of their success. Perhaps if they were to benchmark their performance by means of a DEA model they would be proud to publish their achievements by disclosing more information about themselves.

Social efficiency and geographic location

In this section we explore the relationship between geographical location and efficiency (both social and financial). The subject of country of establishment and commercial bank efficiency has been studied, amongst others, by Berg et al. (1993), and Amel et al. (2004). An earlier study found that MFIs operating in different countries, adapt to the environment in which they work; Gutiérrez-Nieto et al. (2006). In that paper, only Latin American MFIs were studied. If MFIs that operate in different countries of a continent were found to be different, it is expected such differences will be emphasised in the case of MFIs that operate in different continents.

FMIs have been classified into four groups according to the continent in which they operate. These are: Asia, Africa, Latin America, and East Europe. We have studied the differences that exist by means of ANOVA, and a non-parametric test of differences in means. In both cases we have tested the difference in means between a group and the rest of the sample; for example, the difference in means between African and non-African MFIs. The results are summarised in Table 9, where only variables that have revealed significant differences at the 5% level have been reported.

There are 16 Asian MFIs in the sample. The tests show that Asian MFIs have higher efficiency than non-Asian MFIs. These differences are significant in the models of social efficiency ACE-W and ACE-WP. No differences were found in the models of financial efficiency. Digging further into the detail of the figures, we find that the average Asian MFI has about the same average assets as the rest of the MFIs (5,412,740 versus 5,725,557), twice as many employees (186 versus 92), but support four times as many women as the rest (28,439 versus 7,178). This orientation towards

women empowerment must account for the higher social efficiency results, particularly in the model that only includes women (ACE-W).

No significant differences are apparent in social efficiency when the 54 African MFIs are compared to the rest, but significant differences appear in financial efficiency, as measured by ACE-L and ACE-R. African MFIs have significantly lower efficiency averages than the rest under both specifications.

Concentrating now on the 9 Latin American MFIs in the study, no significant differences are found in social efficiency. Significant differences are found in financial efficiency, as measured by ACE-L, ACE-R, and ACE-LR, the average efficiency of Latin American MFIs being higher than the average efficiency of non-Latin American MFIs.

The last set, 9 MFIs, is located in Eastern Europe. The main distinguishing feature of these MFIs is their profitability. They have higher values of ROA and ROE, and have significantly high values of financial efficiency as measured by ACE-L and ACE-R. The down side is that they have lower social efficiency than the rest, as measured by specifications ACE-WP and ACE-P.

In summary, we have found that there are differences between the four regions of the world. Asian MFIs are associated with high social efficiencies; African MFIs reveal low financial efficiency; Latin American MFIs are financially more efficient than the rest; while MFIs located in Eastern Europe are characterised by lower social efficiency levels and higher financial efficiency.

		Significant
Δsia	ANOVA	ACE-W** ACE-WP*
7310	Mann-Whitney U	ACE-W** ACE-WP**
Africa	ANOVA	
Amca	Mann-Whitney U	(ACE-L*) (ACE-R*)
Latin	ANOVA	ACE-LR*
America	Mann-Whitney U	ACE-L* ACE-R** ACE-LR*
Eastern	ANOVA	ROA* ACE-L* ACE-R** (ACE-P*)
Europe	Mann-Whitney U	ROA** ROE* C-R* ACE-L* ACE-R** (ACE-P*) (ACE-WP*)

** Significant at the 0.01 level (2-tailed)

* Significant at the 0.05 level (2-tailed).

Table 9. Tests of differences in means: ANOVA and non-parametric. Grouping variables: Asia vs non Asia, Africa vs non Africa, Latin America vs non Latin America, and Eastern Europe vs non Eastern Europe. Degrees of freedom within groups 87, and total 88. Lower efficiency levels are shown in brackets.

A final analysis emerges from an overall assessment of the results that we have obtained up to now. Can we relate social efficiency, particularly social efficiency involving women, to such aspects as region of activity, performance ratios, and NGO status? To answer this question, a series of regression models were estimated with social efficiency as the dependent variable and performance ratios, area of activity, and NGO status as dependent variables. After appropriate simplifications, the best model found contained only one performance ratio, cost per borrower (C/B), a dummy variable indicating if the MFI was in Asia, and a dummy variable that captured NGO status. All three variables were significantly different from zero, but the adjusted R^2 value was rather low, at 0.292. Thus, social efficiency differences cannot be justified on the basis of organisational structure, costs faced by the entity, or area of activity. This can be interpreted to mean that it is not enough to know the region of activity, the organisational structure, and the costs faced by the entity, and that there is still much to be explained by other aspects of the MFI, such as good management, corporate social responsibility, and knowledge of the issues. . Detailed statistical results can be seen in Table 10.

	$ACE_W_k = \beta_0 + \beta_1 NGO / NonN_k + \beta_2 Asia_k + \beta_3 RatioC / B_k + e_k$			
	Expected sign	Coefficient	t-value	р
Constant		29.083	7.918	0.000
NGO/non-NGO	+	11.455	2.570	0.012
Asia	+	13.962	2.367	0.020
Ratio C/B	-	-0.090	-4.242	0.000

Note: F-statistic = 12.83 (significant at the 0.01 level); adjusted $R^2 = 0.292$.

ACE-W = Social efficiency (women as output) NGO/Non NGO = Dummy variable Asia = Dummy variable Ratio C/B = Operating Cost / Number of active borrowers

 Table 10. Regression results

4. Conclusions

MFIs are at the forefront of the fight against poverty and provide opportunities for women. Much debate has taken place on how to measure their performance. In general, they have been treated as purely financial institutions, and methodologies that are appropriate for commercial banks have been adapted to MFIs. It is sound to expect that an MFI should be financially viable, since unviable institutions cannot meet their social obligations for long. But MFIs have a social role to perform, and also have to be assessed on how well they meet their social responsibilities. No clear methodology exists to measure how far an MFI meets its social obligations.

In this paper we have addressed the issue of MFI social performance measurement and we have taken it one step further by calculating a series of comparative efficiency indexes using Data Envelopment Analysis. This approach has been extended to, and combined, with the analysis of financial efficiency assessment also using Data Envelopment Analysis. The process of defining social outputs has required the creation of an indicator of the extent to which an MFI supports the poor. This indicator combines average loan, number of borrowers, and the average wealth of the country into which the MFI operates.

The models entertained have used three inputs (assets, costs and employees), two financial outputs (loans and revenues) and two social outputs (women and the index of poverty). A series of hypotheses have been entertained, and some of them have been found to be supported by the data. We have found a positive, but low, correlation between social efficiency and financial efficiency. This has led to a categorisation of MFIs according to their strength in financial or in social efficiency. We have found, with one exception, that there are no MFIs that are socially efficient but financially inefficient, something that is consistent with the view that in order to meet their social responsibilities, MFIs have to be financially sound. We have, however, found a series of MFIs whose efficiency is low both from the financial and from the social points of view. These are institutions whose future may not be very bright. Another hypothesis that has been supported by the data is that there is a significant and positive relationship between efficiency in supporting women and efficiency in fighting poverty.

A third hypothesis that has been supported by the data is that Non Governmental Organisations are more socially efficient than the MFIs that are run under other organisational structures. This confirms the findings of earlier studies.

The geographical area of activity of the MFI was also found to be important, also in line with previous studies.

No support was found for another series of hypotheses. No relationship was found between profitability, age, and information disclosure and social efficiency.

All these findings are not confounded by the level of multicollinearity between explanatory variables, as correlations between variables were very low.

An attempt to relate social efficiency to performance ratios, NGO status, and area of activity, produced some significant results, but low values of goodness of fit of measures. Most of the variation in social efficiency performance remains unexplained. This can only be studied at the micro level, by means of case studies that focus on particular MFIs and try to explain what it is that makes them to be efficient or not.

References

Adams, D.W., Von Pischke, J.D., 1992. Microenterprise Credit Programs: Déjà Vu. World Devel. 20 (10), 1463-1470.

Almazan, A. (2002): A Model of Competition in Banking: Bank Capital vs Expertise. J. Finan. Intermediation 11, (1), 87-121.

Amel, D., Barnes, C., Panetta, F., Salleo, C., 2004. Consolidation and efficiency in the financial sector: A review of the international evidence. J. Banking Finance 28, 2493-2519. Amin, R., Ahmed, A.U., Chowdhury, J., Ahmed, M., 1994. Poor Women's Participation in Income-Generation Projects and Their Fertility Regulation in Rural Bangladesh: Evidence from a Recent Survey. World Devel. 22 (4), 555-565.

Athanassoupoulos, A.D., 1997. Service quality and operating efficiency synergies for management control in the provision of financial services: Evidence from Greek bank branches. European Journal of Operational Research 98(2), 300-313.

Berg, S.A., Forsund, F.R., Hjalmarsson, L., Suominen, M., 1993. Banking efficiency in the Nordic countries. J. Banking Finance 17 (2-3), 371-388.

Berger, A.N., Cummins, J.D., Weiss, M.A. Zi, H., 2000. Conglomeration versus Strategic Focus: Evidence from the Insurance Industry. J. Finan. Intermediation 9 (4), 323-362.

Berger, A.N., Humphrey, D.B., 1997. Efficiency of financial institutions: International survey and directions for future research. European Journal of Operational Research 98, 175-212.

Berger, A.N., Mester, L.J., 1997. Inside the black box: What explains differences in the efficiencies of financial institutions? J. Banking Finance 21 (7), 895-947.

Berger, A.N., Mester, L.J., 2003. Explaining the dramatic changes in performance of US banks: technological change, deregulation, and dynamic changes in competition J. Finan. Intermediation 12(1), 57-95.

Canhoto, A,. Dermine, J. 2003. A note on banking efficiency in Portugal, New vs. Old banks. J. Banking Finance 27, 2087-2098.

Casu, B.; Girardone, C. Molyneux, P., 2004. Productivity change in European banking: A comparison of parametric and non-parametric approaches. J. Banking Finance 28 (10), 2521-2540.

Charnes, A., Cooper, W.W., Lewin, Y.A., Seiford, M.L., (Eds), 1990. Data Envelopment Analysis: theory, methodology, and applications. Kluwer Academic Publishers, Dordrecht, The Netherlands. Charnes, A., Cooper, W.W., Rhodes, E., 1978. Measuring the efficiency of decision making units. European Journal of Operational Research 2, 429-444.

CGAP, 2003. Microfinance consensus guidelines. Definitions of selected financial terms, ratios and adjustments for microfinance, 3rd edition. Consultative Group to Assist the Poorest, Washington D. C., USA.

Conning, J., 1999. Outreach, sustainability and leverage in monitored and peermonitored lending. J. Devel. Econ. 60, 51–77.

Copestake, J., Bhalotra, S., Johnson, S., 2001. Assessing the impact of microcredit: A Zambian case study. J. Devel. Stud. 37 (4), 81-100.

Daley-Harris, S., 2004. State of the Microcredit Summit Campaign Report 2004. Microcredit Summit Campaign.Washington D.C., USA.

Dichter, TW., 1996. Questioning the Future of NGOs in Microfinance. J. Int. Devel. 8 (2), 259-269.

Dunford, C., 2000. The Holy Grail of Microfinance: 'Helping the Poor' and 'Sustainable'? Small Enterprise Development 11 (1), 40-44.

English, M., Grosskopf, S., Hayes, K., Yaisawarng, S., 1993. Output allocative and technical efficiency of banks. J. Banking Finance 17, 349-66.

Goddard, J., Molyneux, P., Wilson, J.O.S., 2004. Dynamics of growth and profitability in banking. J. Money, Credit, Banking 36 (6), 1069-1090.

Goetz, A.M., Gupta, R.S., 1996. Who takes the credit? Gender, Power and Control over Loan Use in Rural Credit Programmes in Bangladesh. World Devel. 24 (1), 45-63.

Gutiérrez-Nieto, B., Serrano-Cinca, C., Mar Molinero, C., 2006. Microfinance Institutions and Efficiency. Omega, forthcoming, doi:10.1016/j.omega.2005.04.001

Hashemi, S.M., Schuler, S.R., Riley, A.P., 1996. Rural Credit Programs and Women Empowerment in Bangladesh. World Devel. 24 (4), 635-653.

Hulme, D., Mosley, P., 1996. Finance against Poverty. 2 Volumes. Routledge, London.

Hulme, D., 2000. Impact Assessment Methodologies for Microfinance: Theory, Experience and Better Practice. World Devel. 28 (1), 79-98.

Kao, C., Liu, S.-T., 2004. Predicting bank performance with financial forecasts: A case of Taiwan commercial banks. J. Banking Finance 28 (10), 2353–2368.

Karim, M.R., Osada, M., 1998. Dropping out: An emerging factor in the success of Microcredit-based poverty alleviation programs. Developing Economies 36 (3), 257-288.

Luo, X., 2003. Evaluating the profitability and marketability efficiency of large banks. An application of data envelopment analysis. J. Bus. Res. 56, 627-635.

Mahmud, S., 2003. Actually how Empowering is Microcredit? Devel. Change 34 (4), 577-605.

Matin, I., Hulme, D., Rutherford, S., 2002. Finance for the Poor: From Microcredit to Microfinancial Services. J. Int. Devel. 14 (2), 273-294.

Miller, S.M., Noulas, A.G., 1996. The Technical Efficiency of Large Bank Production. J. Banking Finance 20, 495-509.

Morduch, J., 1999a. The microfinance promise. J. Econ. Lit. 37, 1569-1614.

Morduch, J., 1999b. The role of subsidies in microfinance: evidence from the Grameen Bank. J. Devel. Econ. 60, 229–248.

Morduch, J., 2000. The Microfinance Schism. World Devel. 28 (4), 617-629.

Mosley, P., 2001. Microfinance and poverty in Bolivia. J. Devel. Stud. 37 (4), 101-132.

Navajas, S., Schreiner, M., Meyer, R.L., González-Vega, C., Rodríguez-Meza, J., 2000. Microcredit and the poorest of the poor: Theory and Evidence from Bolivia. World Devel. 28 (2), 333-346.

Oral, M. and Yolalan, R., 1990, An empirical study of measuring operating efficiency and profitability of bank branches, European Journal of Operational Research 46, 282-294.

Panjaitan-Drioadisuryo, R.D.M., Cloud, K., 1999. Gender, self-employment and microcredit programs. An Indonesian case study. Quart. Rev. Econ. Finance 39 (5), 769-779.

Parsons, L. M., 2003. Is Accounting Information From Nonprofit Organizations Useful to Donors? A Review of Charitable Giving and Value-Relevance. Journal of Accounting Literature 22, 104-129.

Pastor, J.M., 1999. Efficiency and risk management in Spanish banking: a method to decompose risk. Appl. Finan. Econ. 1999; 9(4), 371-384.

Rankin, K. N., 2001. Governing development: neoliberalism, microcredit, and rational economic woman. Economy Society 30 (1), 18-37.

Sealey, C.W., Lindley, J.T., 1977. Inputs, outputs and a theory of production and cost at depository financial institutions. J. Finance 32, 1251–1266.

Seiford, L.M., Zhu, J., 1999. Profitability and marketability of the top 55 U.S. commercial banks. Management Science 45 (9), 1270-1288.

Sherman, H. D Gold, F., 1985. Bank branch operating efficiency: Evaluation with Data Envelopment Analysis. J. Banking Finance 9 (2), 297-315.

Smith, S.C., 2002. Village Banking and Maternal and Child Health: Evidence from Ecuador and Honduras. World Devel. 30 (4), 707-723.

Soteriou, A., Zenios, S.A., 1999. Operations, quality and profitability in the provision of banking services. Management Science 45 (9), 1221-1238.

SPI, 2003. Social Performance Indicators for the Financial Industry. [on line] spifinance.com<<u>http://www.spifinance.com/SPI_Finance_2002.pdf</u>> (04/04/05).

Thanassoulis, E., 2001. Introduction to the theory and application of data envelopment analysis. Kluwer Academic Publishers, Dordrecht, The Netherlands.

Todd, H. 1996. Women at the Center: Grameen Bank Borrowers after One Decade, in: Shahidur, R.K., Fighting Poverty with Microcredit: Experience in Bangladesh. Oxford University Press, New York, pp. 183-185.

Tucker, M., 2001. Financial Performance of Selected Microfinance Institutions. Journal of Microfinance 3 (2), 107-123.

Tulkens, H. 1993, On FDH efficiency analysis: Some methodological issues and applications to retail banking, courts and urban transit, J. Productiv. Anal. 4, 183-210

Vassiloglou, M. and Giokas, D., 1999. A study of the relative efficiency of bank branches: An application of data envelopment analysis, Journal of the Operational Research Society, 41, 591-597.

Woller, G.M., Dunford, C., Woodworth, W., 1999. Where to Microfinance? International J. Econ. Devel. 1 (1), 29-64.

Wheelock D., Wilson, P.W., 1999. Technical progress, inefficiency, and productivity change in US banking, 1984–1993. J. Money, Credit, Banking 31 (2), 212-234.

Worthington A., 1998. The determinants of non-bank financial institution efficiency: a stochastic cost frontier approach. Appl. Finan. Econ. 8 (3), 279-287.

Yaron, J., 1994. What Makes Rural Finance Institutions Successful? The World Bank Res. Observer 9(1), 49-70.

Zeller, M, Sharma, M, Henry, C, Lapenu, C. 2002. An operational tool for evaluating poverty outreach of development policies and projects, in: Zeller, M., Meyer, R.L. (Eds), The Triangle of Microfinance. John Hopkins University Press, Baltimore and London, pp. 172-195.



http://www.kent.ac.uk/kbs/research-information/index.htm