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Taylor and Francis Ltd.
2013

Kar, A K 2013, 'Double bottom lines in microfinance : are they mutually exclusive?', Journal of Small Business and Entrepreneurship, vol. 26 , no. 1, pp. 87-107. https://doi.org/10.1080/08276331.2012.761804

http://hdl.handle.net/10138/569471
10.1080/08276331.2012.761804

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Double Bottom-lines in Microfinance: Are They Mutually Exclusive?

Ashim Kumar Kar*

Abstract

Microfinance institutions (MFIs) are generally constrained by double bottom-lines: keep the original social mission intact by serving the poor (the first bottom line) and attain financial sustainability (the second bottom line). However, these two bottom-lines can be mutually exclusive in effect. This paper demonstrates how factor analysis, a multivariate statistical tool, can be utilised to examine this conjecture. First, factor analysis is used to construct two simulated performance indicators combining original variables, each one representing a distinct dimension of performance. Then individual scores ascribed to MFIs on each factor are used as the dependent variables of two simultaneous-equations models that present new evidence on the determinants of MFIs' performance and mission drift.

Keywords: Microfinance, outreach, sustainability, panel data estimation, factor analysis.

To cite this article:
Kar, A. K. (2013). Double bottom lines in microfinance: are they mutually exclusive? *Journal of Small Business and Entrepreneurship*, *26* (1), 87-107.
https://doi.org/10.1080/08276331.2012.761804

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1. Introduction

Microfinance institutions (MFIs) strive for better economic lives of the poor—especially women—in many parts of the developing world. Because of tremendous growth in this industry during the past few decades, MFIs now reach well over 205.3 million clients worldwide with 82.3% of them being women (Maes and Reed, 2012). An MFI is generally constrained by double bottom-lines: keep the original social mission intact (the first bottom line) and ensure financial self-reliance (the second bottom line). However, the win-win proposition of having both of them met is often questioned (Armendariz de Aghion and Morduch, 2005) and these two bottom-lines can be mutually exclusive in effect.

Does excessive profit motive leads MFIs to leave their original social mission of serving the poorest? Is there any trade-off between social performance and financial self-reliance? These are the questions observers frequently ask while expressing their concerns over mission drift in microfinance. They are indeed concerned whether better financial performance comes at the cost of social mission. The welfarist versus institutionist schism is centred on this concern. The institutionists suggest that a profit-oriented microfinance industry is better able to serve the poor as it calls for more efficiency and enthusiasm in seeking new markets and loan products (Schreiner, 2002; Christen and Drake, 2002; Rhyne, 1998). Therefore, MFIs should be supported by subsidies only initially and get rid of subsidy dependency by making some profits as they grow. The welfarists, on the contrary, are concerned that outreach to poorer customers declines as MFIs become increasingly profit-motivated (Hermes et al., 2008; Woller, 2002).

Empirical studies which have rigorously attempted to address this issue are small in number and mostly provide mixed results. Some of the first round works support the position that a more profit-oriented microfinance industry is better able to serve the poorest (Gonzalez-Vega et al., 1996; Christen, 2001; Littlefield et al., 2003; Campion et al., 2001). Also, recent studies of Hishigsuren (2007), Cull et al. (2007) and Mersland and Strom (2010) did not find convincing evidence in support of mission drift. However, others have supported the view that increased profit motivation indeed leads MFIs to shift away from their original social mission of serving the poorest (Paxton et al., 2000; Rhyne, 2001; Woller et al., 1999; Woller, 2002). So, this area requires new and intensive research possibly employing new techniques as described below.

In the literature, mission drift is frequently expressed in terms of MFIs' increased tendency of extending larger loans while they scale up. Accordingly, average loan size has been widely used as a proxy for mission drift in microfinance (Mersland and Strom, 2010; Cull et al., 2007; Schreiner, 2002). Alternatively, few studies have also used average loan amount adjusted by GDP or GNI per capita. However, increase in average loan size alone may not always indicate mission drift. Average loan size may increase over time due to other reasons too. Two already well-known propositions—progressive lending and cross-subsidization—might be of help in explaining this trend. Progressive lending indicates a situation where existing loan clients can reach out higher credit ceilings after observing a clean repayment record at the end of each credit cycle. Cross-subsidization refer to the use of gains from profitable wealthier borrowers (generally served with bigger loans) to subsidize losses from unprofitable poor borrowers (normally served with smaller loans). However, mission drift occurs if an MFI increases its average loan size and/or reaches out to wealthier clients neither for progressive lending nor for cross-subsidization reasons (Armendaritz and Szafarz, 2009). Again, Mosley (1996) and Schreiner (2002) emphasized using the percentage of women borrowers, rural loan clients or average loan size as the substitutes for MFIs' social performance. Mission drift implies shifting away from these social performance measures as well (Mersland and Strom, 2010).

However, the above proxies for depth of outreach have some limitations. Share of women borrowers is a useful gender related performance indicator, but isolating clients as rural or urban can sometimes be difficult as the justifications behind such classification are to some extent ambiguous. For instance, the client may borrow from a village-level MFI branch, but work in an urban set-up or vice versa. Similarly, average loan size is a very crude measure in itself. Average loan amount may not be enough to reflect the true financial position of the client unless it is adjusted by any common national income measure. Regarding financial performance of MFIs, several indicators are currently in use too. For example, operational self-sufficiency, financial self-sufficiency, return on assets and return on equity are used to measure MFIs' overall financial performance. Several studies have also employed efficiency variables (e.g., cost per borrower, cost per loan and cost per dollar lent), risk variables (e.g., portfolios-at-risk and write-off ratio) and productivity variables (e.g., borrower per staff member and borrower per loan officer) as performance indicators.

Clearly, use of different proxies brings about diverse research outcomes. Therefore, single indicators, combining many variables, are required for measuring MFIs' social and financial performance. Combined indicators can then be easily used in empirical exercises to check whether they are mutually exclusive and how far the concerns for mission drift are credible. However, very few attempts have been made to combine these indicators as yet. Zeller et al. (2003) provides an outline for combining different measurement indicators and suggested that giving weights, arbitrary or derived through multivariate techniques (e.g., principal components analysis), can be a solution to combine variables. So far, to the best of our information, the study of Weber and Ferro Luzzi (2007) has been the first such attempt. Generalising the second method of Zeller et al. (2003) and utilising data on 45 MFIs, they applied factor analysis to a set of social and financial performance indicators. However, no study so far has addressed the mission drift issue employing this technique. Also, country-specific challenges have never been addressed using this type of aggregated performance scores in previous studies. This study aims to fill the research gap. The study also attempt to demonstrate how factor analysis, a multivariate statistical tool, can be utilised to this end.

Accordingly the methodology pursued in this study has a few steps. Firstly, we create artificial indices for both dimensions of MFI-performance using confirmatory factor analysis (CFA). Using CFA is justified as we want to test the specific hypothesis on the number of dimensions underlying a set of variables in the dataset. Put differently, we conjecture that there are two dimensions of MFI-performance in the database and we seek to test them. In the second step, MFI scores for each of these indices are computed which are later used as the dependent variables in two models. Firstly, in a so-called seemingly unrelated regression (SUR) model to explore the determinants of MFI performance and then in another simultaneous equations model to examine whether there is any trade-off between the social and financial performance scores, commonly known as mission drift in microfinance.

The remainder of the chapter is organized as follows. Section 2 describes the data. Section 3 discusses the theoretical foundation of factor analysis and the results obtained by applying this technique to our data. In section 4, estimation strategies applied in the study are explained. Section 5 presents results concerning the determinants of MFI performance and mission drift issues. Robustness analysis is provided in section 6. Finally, section 7 provides discussions and conclusions.

2. Data description

The study utilises relevant data on MFIs collected from the Microfinance Information eXchange (MIX) database, a web-based and so far the largest global information platform for the microfinance industry. The sample contains 113 MFIs in 47 countries over a period of 8 years (2000-2007). After making necessary adjustments for missing data the main sample consists of 904 observations. A second panel dataset used in the study includes 67 MFIs in Bangladesh for 5 years—from 2003 to 2007. We also utilised a third dataset containing a cross-section of 426 MFIs in 81 countries where most of the observations are from 2007. Results from the latter two datasets are mainly for robustness checks to authenticate the main findings.

A total of six variables have been used to perform the confirmatory factor analysis. Operational self-sufficiency (OSS), return on assets (ROA) and self-sufficiency index (SSI)[1] are primarily the indicators of overall financial performance or sustainability of MFIs. Remaining three variables—average loan size (LBB), average loan size adjusted by GNI per capita (LBBGNI) and percent of female loan clients (WOMBORR)—are the proxies for MFIs' depth of outreach. LBB is the most widely used proxy for measuring depth of outreach and as generally perceived, the smaller its size the better the depth of outreach (Cull et al., 2007; Schreiner, 2002). However, as stated above, LBB per se may not represent the true economic position of the borrower unless it is either compared with or adjusted by any standard national income measure. Consequently, LBBGNI is used as a better measure for depth of outreach in the analysis alongside LBB, the unadjusted average loan variable. Again, as women are generally the poorest of the poor, higher percentage of female borrowers indicates better depth of outreach (Schreiner, 2002). For this reason, targeting the women has been a priority strategy in Grameen Bank since its beginning for instance (Dowla and Borua, 2006). So, the WOMBORR variable has also been used as a proxy for depth of outreach in the analysis.

(Table 1)

(Table 2)

For financial performance of MFIs, OSS, ROA and SSI have been employed in the analysis. Operational self-sufficiency is the ratio of total financial revenue and total financial expense,

[1] Following Ahlin and Lin (2006), we computed the self-sufficiency indices. The formula for the index in terms of operational self-sufficiency is:
S*ufficiency index* = Operational self-sufficiency / (1+ Operational self-sufficiency).

which includes impairment loss and operating expense. Hence, a number greater than one (or equivalently greater than 100%) indicates that the MFI has sufficient revenue from lending to cover its costs, including the cost of capital, accounting or bad loans and operating expenses. Thus, OSS measures how well the MFI can cover its costs through operating revenues. It is a better indicator for measuring MFI-performance than ROA, for example. Because ROA, another measure for financial sustainability, is basically self-reported and does not necessarily include the value of donations, in-kind subsidies and inflation those MFIs should incorporate in this ratio. Additionally, employing OSS we have calculated SSI as another index which represents MFIs' self-sufficiency. While OSS equals revenue/expense, SSI equals revenue/(revenue+expense). Such transformation can overcome possible outlier problems (Ahlin and Lin, 2006). In addition to OSS and SSI, however, we have also utilised ROA, the classical measure for performance, to complete the search for a composite financial performance indicator. Variables have been described in Table 1 and Table 2 and descriptive summary statistics of used variables are given in Table 3.

(Table 3)

3. Factor analysis

3.1 The application of factor analysis

Factor analysis basically aims at representing a variable z_j in terms of several underlying factors, or hypothetical constructs. In order to describe a variable in terms of several others, the simplest mathematical representation is a linear one and in this paper we assume linearity. Within this linear model we aim (a) to extract the maximum variance and (b) to maximally reproduce the observed correlation. The basic factor analysis model is:

$$Z_j = a_{j1}F_1 + a_{j2}F_2 + \ldots\ldots + a_{jm}F_m + u_jY_j \quad (j = 1, 2, \ldots\ldots, n);\ m < n \qquad (1)$$

Where, each of the n observed variables is described linearly in terms of m common factors and a unique factor. The common factors account for the correlations among the variables, while each unique factor accounts for the remaining variance (including error) of that variable. The coefficients of the factors are frequently referred to as loadings. In the matrix notation model (1) above can be expressed as:

$$Z = A.f + s \qquad (2)$$

Where all observed variables are included in the Z vector, A denotes the matrix of factor loadings, f represents the vector of common factors and s includes the variables' unique factors. Thus, factor analysis can be utilised to analyse interrelationships among a large number of variables and to explain these variables in terms of their common underlying dimensions or factors.

As stated earlier, MFI-performance is assessed mainly by using two indicators—outreach and sustainability. Both of these variables, again, are interpreted in terms of several other observable variables (Hartarska, 2005). Utilising interrelationships among observable variables, factor analysis generates corresponding simulated indicators for each dimension taking into account both social (outreach) and financial (sustainability) aspects. So, we can comfortably utilize factor analysis in the context of MFIs' performance. However, two important points need further elaboration. First, in order to get an unbiased correlation matrix basically all variables involved in the factor analysis need to be continuous and are assumed to be normally distributed. This will help identifying factors which underlie the variables. In this analysis all variables used are continuous and mostly normally distributed as required. Therefore, unless otherwise, Pearson's correlation matrix will not be biased and it can be used as the starting point of the factor analysis.

Second, in a factor analysis generally the factor loadings matrix A is not determined uniquely and we need to impose constraints on the parameters in the original model to get a solution. However, a transformed model, obtained through the process of factor rotation, can offer a more interpretable solution. We assume that social commitment and financial performance of MFIs are not independent. Therefore, we will exploit the oblique rotation method that can better handle such correlation structure (Weber and Ferro Luzzi, 2007). Finally, after rotation of factors is done and representation of the data in this form is considered adequate, every MFI can be ascribed a score on each derived factor that will later be used for regression analysis.

3.2 Correlation coefficients

As mentioned previously, the main sample of this exercise contains data for eight years ranging between 2000 and 2007. We explored factor analysis for each of the years separately. Maximum likelihood factoring maximises the determinant of the partial correlation matrix, and unlike other factoring, provides formal hypothesis tests that help determine the appropriate number of factors[2]. Hence this solution is also meaningful as a descriptive method for non-normal data[3]. Thus, we determined the appropriate number of factors through maximum likelihood factoring and then employed the principal-components factor to conduct the analysis. However, while similar analyses have been conducted for each of the available years, results for only one year are displayed in several instances mainly for the sake of brevity. For example, the Scree-plot in Figure 1 corresponds to the year 2003. This is logical since results are mostly identical and comparable across years[4].

There are four basic steps in any standard factor analysis. They are (a) data gathering and generating the correlation matrix, (b) extraction of initial factor solution, (c) rotation and interpretation and (d) construction of scales or factor scores to be used in further investigations and analyses. As the first step, Table 4 presents correlation coefficients among the selected variables for 2005, which quite convincingly confirms that the first three variables—LBB, LBBGNI and WOMBORR—belong to a similar group, as correlations among these variables are quite high in absolute value. Similarly, correlations among the remaining three variables—OSS, SSI and ROA—are also very high in absolute values. However, quite the reverse, their correlations with the depth of outreach variables are very weak. Therefore, it is quite rational to expect that the former three 'depth of outreach' indicators will form a dimension that may represent the social commitments, or performance, of MFIs. Likewise, the latter three variables will constitute a different dimension that concerns to the sustainability or financial performance of MFIs. As mentioned above, this matrix of correlations is then used to extract the factors via both maximum likelihood factoring and principal-components factors.

(Table 4)

3.3 How many factors to be retained in a factor analysis?

As the second step in a standard factor analysis, we now need to choose the appropriate number of latent factors while applying the confirmatory factor analysis (CFA). Some standard statistical and visual tools are frequently used, either individually or in concert, to help us select

[2] Two chi-square values (chi-square with (n+k) degree of freedom and chi-square with n degrees of freedom, where n stands for the number of observations and k stands for the number of parameters) for formal likelihood ratio tests are obtained and high p-value fails to reject the null that the model for any specific number of factors is not significantly worse than the full-fit model.
[3] We assumed normality in our data. As a check, however, maximum-likelihood factoring is used.
[4] Additional results are available from the author through personal requests.

the appropriate number of factors to retain. The following rules are noteworthy as they are often used in applied works[5].

Kaiser's eigenvalue-greater-than-one rule: Kaiser's (1960) eigenvalue-greater-than-one rule, possibly the best known and most utilised one, suggests retaining only those factors that have eigenvalues greater than one. In other words, this method suggests excluding factors with eigenvalues smaller than one, since the factors retained in this way account for more variance than the average for the variables. Given that an eigenvalue is the amount of variance explained by one more factor, it really does not make sense to add a factor that explains less variance than is contained in one variable.

Cattell's Scree test: Cattell (1966) suggests another popular approach that entails visual examination of a plot, called the scree-plot, where the eigenvalues are presented in a descending order and a line connects them. Subsequently, the graph is examined to determine where the line levels off. The highest number of factors to extract is the point at which the curve bends, or where the elbow is. We retain the number of factors up to the ["elbow" – 1]. Figure 1 shows how an examination of this scree plot of the eigenvalues against the corresponding factor numbers can help choose the number of factors.

Variance Explained Criteria: This rule suggests retaining only adequate factors so that the cumulated variance explained is no less than 70 per cent.

Chi-square test: Overall goodness-of-fit of the factor analysis model can be tested through maximum likelihood (ML) or generalised least-squares (GLS) factor extraction methods. Here, the number of factors is utilised as its null hypothesis. That is, the null hypothesis of the LR chi-squared test is that the factor analysis model fits the data. So, a non-significant model test is desirable, whereas a statistically significant chi-square test means that more factors are needed to account for the structure of the data.

[5] These approaches are suggestive, of course, not inclusive. Other important rules, for example, include: Velicer's (1976) Minimum Average Partial (MAP) test and Horn's (1965) Parallel Analysis. However, it is extremely important to remember that most of the above rules are someway ad hoc and subjective. All methods have several deficiencies. For limitations of these methods see, for example, Ledesma and Valero-Mora (2007). Therefore, it is always better not to rely on any single method or rule, but to evaluate and determine the solution as a complete picture on the basis of all of the methods employed. Hence, we exercised several methods.

Table 5 presents the eigenvalues and the associated proportion of variance explained by each underlying factor for the sampled years—2000 to 2007. Results confirm that a two-factor choice is fairly logical. Indeed, applying all of the above-mentioned criteria the two-factor solution seems the best for each year for the existing dataset. Firstly, for every year we get two eigenvalues larger than one. Secondly, retaining only two factors guarantees a cumulated variance of 70 per cent. Finally, the scree-plot in Figure 1 shows that the third and subsequent eigenvalues are situated on a straight-line, which again confirms a two-factor solution [(factors up to the "elbow"=) 3 – 1 = 2].

(Table 5)

(Figure 1)

Subsequently, rotation of factors has been applied to offer an easily interpretable and more significant solution loadings matrix. As mentioned above, it is quite logical to expect that different dimensions of performance are correlated. An oblique rotation of factors can handle this situation and we therefore apply that method to introduce correlations between factors. Table 6 presents the rotated factor loadings which are very similar across the years.

Table 6 shows that OSS, SSI and ROA load positively and quite significantly on the first factor. So, higher values of these variables lead to higher scores on factor-1. Since a higher level of financial sustainability is associated with higher values of OSS, SSI and ROA this factor is clearly related with financial performance of microfinance institutions. We therefore label this factor financial performance. Again, LBB and LBBGNI load quite strongly and positively on the second factor, indicating that higher values of these variables lead to higher scores on factor-2. On the contrary, WOMBORR variable load heavily and negatively on the second factor, meaning that MFIs which have a smaller value for this variable will have a higher score on factor-2, other things being equal. Since a deeper outreach is associated with higher female participation and also with a smaller value of LBB and LBBGNI variables, factor-2 clearly reflects the social dimension of performance and can be termed as social performance. It should be noted here that depth of outreach increases as LBB and LBBGNI decreases and as WOMBORR increases. Therefore, the former two variables loaded positively and the later one loads negatively on factor 2, which quite convincingly seem rational.

(Table 6)

4. Estimation strategy

4.1 Determinants of MFI performance

What are the determining factors of MFI performance and why they differ? While a large number of MFIs are doing quite well, why others are lagging behind? These are the questions commonly asked while measuring MFI performance. This section attempts to answer these questions by using the synthetic measures for MFI performance obtained through the factor analysis exercise already—financial performance and social performance—as the outcome variables of a model. Thus, quite similar in spirit to Weber and Ferro Luzzi (2007), performance of MFIs is conjectured as follows:

$$S_{ji} = X_{ji}\beta_j + Z_{ji}\gamma_j + \varepsilon_{ji} \qquad (3)$$

Where, S_{ji} is the performance of MFI i (=1,2, ..., 113) on dimension j (=1, 2)[6]; X_i is a row vector of MFI i's performance as explained by social and financial dimensions; Z_{ji} includes variables assumed to affect either one of them. We assume the following: E $(\varepsilon_{1i}, \varepsilon_{2i}) = \sigma_{12} \neq 0$, since we assume that there is a trade-off between MFIs' social performance and financial performance. So, estimation with the SUR model is ideal here. Several factors may affect these two dimensions of MFI-performance scores. Some of them have effects on both of the dimensions while others can influence only on one of the dimensions. Table 2 describes variables which may affect the performance variables.

Scale of operation is very important for MFIs' cost-effectiveness as scale affects both the breadth of outreach and profitability. Besides, the number of active borrowers, which also represents an MFI's scale of operation, may influence MFI-performance. Therefore, in order to capture the scaling up effect, both of these indicators are included in the analysis. However, some uncertainties are there concerning whether scale affects financial performance and social performance of MFIs positively or negatively.

Financial performance and efficiency of an MFI are related. Broadly defined, a firm is efficient for certain quantities/prices of inputs if it maximises the quantity/price of an output; then again, it is efficient if it operates with the least quantity or least costs of inputs for a given

[6] There are two performance dimensions: social performance and financial performance.

quantity/price of output (Balkenhol, 2007). In microfinance literature several indicators are currently in use as proxies for efficiency. This paper utilizes operational expense to gross loan portfolio ratio and cost per borrower as the proxies for efficiency. We conjecture that both measures of efficiency should affect MFIs' financial performance negatively. But whether the effects of the efficiency measures on social performance would be similar cannot be guessed beforehand.

Two commonly used risk measures—portfolio-at-risk past 30 days (PAR30) and write-off ratio—have been included in the model. Their hypothesised relationship with financial performance indicator is obviously negative. However, the hypothesized link between the risk measures and social performance variable is ambiguous (Mersland and Strom, 2010). MFI-experience and MFI-size have also been incorporated in the model. We hypothesise that the former is negatively associated with the social performance of MFIs. However, its conjectured relationship with financial performance and the relation between MFI-size and both of the performance scores are, once again, uncertain. The study also includes two other control variables—NPNGO and rated. As non-profit status of NGOs literally means that they are not-for-profit, financial performance of MFIs is negatively affected by the NPNGO status. On the contrary, rating should affect financial performance positively because a rated MFI should enjoy a better financial condition getting funding uninterruptedly and hence, better rating implies better financial performance.

In applied research, we often encounter similar model specifications with different outcome variables. If a single database is used for estimating these models the errors may be correlated across the equations and the zero-conditional-mean assumption remains unmet. In these cases, we may want to estimate the models jointly to impose or test cross-equation restrictions and to gain efficiency since we might expect the error terms across equations to be contemporaneously correlated. This is a situation where seemingly unrelated regressions (SURs) can be used, which is an extension of the linear regression model that allows correlated errors between equations[7].

Several problems are likely to plague our panel data models. Heteroskedasticity problems arise from group-wise differences and often taking group means can remove heteroskedasticity. The

[7] Alternatively, a three-stage-least-squares model could be used.

use of a heteroskedasticity-consistent covariance estimator with ordinary least squares estimation in fixed-effects models can yield standard errors robust to unequal variance along the predicted line (Wooldridge, 2002). Existence of autocorrelation within the panels from one time period to another is also a reality.

The study uses an unbalanced panel database and to address the abovementioned problems employs three estimation techniques for the SUR model—SUR estimation on the pooled data, feasible generalised least squares (FGLS) estimation corrected for panel-specific AR1 correlation and Prais-Winsten models with panel-corrected standard errors. FGLS and Prais-Winsten models have been used for HPAC-SUR (panel heteroskedasticity, panel autocorrelation, and contemporaneous correlation adjusted seemingly unrelated regression) solution for contemporaneously correlated error terms. Estimation results are presented in Table 7. Regarding the validity of choice of SUR specification it may be mentioned that the value of the chi-squared statistics are quite high; so, we reject the null hypothesis that the errors are not correlated across equations ($\sigma_{12} = 0$); that is, we reject the hypothesis of independence of the errors terms. Therefore, SUR modeling is appropriate.

4.2 Mission drift

To examine whether the mission drift hypothesis is true, we estimate the following model:

$$SP_{it} = \beta_1 FP_{it} + \beta_2 CPB_{it} + \beta_3 Risk_{it} + \beta_4 Age_{it} + \beta_5 Size_{it} + Constant + \varepsilon_i + u_{it} \quad (4)$$

Where, SP (social performance) and FP (financial performance) are two synthetic performance scores that replace similar variables typically used to measure the depth of outreach and financial sustainability of MFIs respectively; MFI-size, MFI-age, cost per borrower and Risk (PAR30 is used as a proxy) represent other control variables included in the model. The subscripts i,t indicate MFI i (i = 1, 2,.........., 113) in the year t (t = 2000,........, 2007), ε_i is the time invariant characteristic of MFI i, for instance, the country where the MFI is located, and u_{it} is the idiosyncratic error term.

However, financial performance, average cost and loan delinquency measures are simultaneously determined with social performance. So, we should take care of this endogeneity bias. Estimation through instrumental variables may remove this bias if we find a set of relevant instruments that are independent of the disturbance term. For over-identifying restrictions to estimate the coefficients β_j (j=1,...,5), number of instruments (L) should be at least equal to the number of regressors (K). However, longitudinal data are advantageous regarding construction of instruments. It is possible to find instruments among the lagged explanatory variables in panel data and by assumption the lagged variables are not linked with the error terms. However, the lagged values have to be associated with respective regressors. Hansen's (1982) J-test is used to test whether the instruments are independent of the error terms, where J ~ $\chi 2$ with (L-K) degrees of freedom. A high $\chi 2$ value or low p-value indicates that endogeneity is still present and anyhow some of the instruments are correlated with the error term.

Wooldridge (2002) suggests that with the optimal weighting matrix generalised method of moments (GMM) estimators allow for arbitrary heteroskedasticity and serial-correlation for large N (number of cross-section units) and small T (number of time periods). This condition is fulfilled in our case as we have N=113 and T=8 (maximum). So, we perform GMM estimations. Several panel estimation methods—fixed-effects, random-effects, maximum likelihood estimator (MLE) and first-difference—have been applied in this exercise. In fixed effects estimation individual MFI averages are deducted from yearly observations so that individual MFI heterogeneity as fixed-effects is assumed a constant-term's element. Then regression on these transformed variables is executed. Rather than assuming ε_i as part of the constant term, in random-effects estimation the ε_i is considered as a part of a composite error term. For a fixed dataset and underlying probability model, MLE chooses those parameter values that make the data "more likely" than any other parameter-values would make them. In first-difference estimation the difference in social performance, the outcome variable, is regressed on similar differences in explanatory variables. The fixed effect ε_i is removed here too. Applying all these panel data methods enhances the credibility in estimation results.

5. Results

5.1 Determinants of MFI performance

5.1.1 Financial performance

As Table 7 shows, gross loan portfolio (GLP)—the scale-of-operation variable—influences financial performance of the sampled MFIs positively and significantly. This indicates that financial performance of MFIs improves as they scale up, all else being equal, as larger loan portfolios reduce delivery costs. However, for another scale-of-operation variable—number of active borrowers (NAB)—this impact is negative. This is as expected and in line with Weber and Ferro Luzzi (2007). Small loans lead to a rise in costs per client and clearly, as the number of borrowers increases, higher costs negatively affect MFIs' financial performance.

As expected, coefficients for cost per borrower (CPB), the efficiency variable, are negative and highly significant. Coefficients for the cost per dollar lent (OELP) variable, another efficiency measure, are also negative although the relationship is statistically insignificant. A negative relationship between financial performance and efficiency measures reflects the fact that higher costs are unfavourable in attaining financial sustainability. The risk variables—PAR30 and write-off ratio—are also negatively and significantly linked with the financial performance scores. This was not beyond our expectations although impacts of risk factors on financial performance are generally uncertain. More risky portfolios can harm profitability and as a result, cause overall financial performance of the sampled MFIs to decline.

The size variable has negative and highly significant coefficients. Understandably, size should have some influence on financial performance although we could not guess whether such influence would be positive or negative in advance. This confirms that all large firms are not profitable and all small enterprises are not unprofitable either. Size actually is immaterial in terms of attaining profitability and financial viability. Coefficients for the regional dummies confirm clear regional differences in financial performance. Negative and significant coefficients for EAP and SA, for example, confirm that financial performance of the sampled MFIs in these regions are not very well in comparison with the control category (LAC). The legal status variable NPNGO (non-profit NGO) is also included in the analysis to check whether non-profit status is a key determinant of financial performance of MFIs. As expected, coefficients for this variable are negative and highly significant, which suggests that non-profit status is harmful for the financial viability of the sampled MFIs. However, rating improves financial performance as the coefficients for this variable are positive and highly significant.

5.1.2 Social Performance

We now turn to the social performance regressions. The dependent variable here represents MFIs' depth of outreach and this variable is synthesised by positive loadings of two average loan size variables (LBB and LBBGNI) and by negative loadings of the percentage of female borrower variable. Since a decrease in average loan size or an increase in percentage of female borrowers would improve depth of outreach, we need to analyse these results very carefully.

Negative coefficients mean increase in depth of outreach and vice versa. We see that coefficients for the scale-of-operation variable (GLP) are significant and equally positively signed in all model specifications. This confirms credibility of the results and indicates that increased gross loan portfolio may not improve social performance of the sampled MFIs. On the other hand, coefficients for NAB are negative and significant in all models. These suggest that with an increased level of clientele base the depth of outreach improves. One plausible explanation for this may be the fact that the higher the clientele base the higher the possibility of poor customers being included in credit programmes.

The cost variables have different signs suggesting that their impacts are non-monotonic and this warrants some explanation. Here a positive coefficient for the cost-per-borrower variable indicates that the higher the cost the lower the depth of outreach. Although this apparently seems unconvincing, this is justified because as average costs increase obviously an MFI tries to minimise that cost by increasing the clientele base. Again, negative OELP coefficients imply that with decreasing costs-per-dollar-lent, overall depth of outreach increases. This is plausible because if increasing clientele base is of no use then the MFI should try other channels including reducing operating costs.

The included risk variable (PAR30) has positive significant coefficients which mean that with an increased level of portfolio risk, depth of outreach declines. This is quite logical as with a higher level of risk the MFI will switch to better-off clients because then repayments are much guaranteed. Among other variables here the 'size' variable is positive significant and the age variable is negative significant. A positive coefficient for the size variable indicates that the larger the size the lower the depth of outreach, which increases the concerns for mission drift. A negative coefficient for the age variable suggests that more experienced institutions are doing well in terms of depth of outreach. This was expected, as without ensuring social performance an MFI cannot be sustain for a long time. Coefficients for the regional dummies are mostly positively signed and highly significant for EAP and SSA regions. Therefore, social performance of the MFIs in these regions is not very well in comparison with the control category LAC. However, non-profit NGO status improves the depth of outreach or social performance as expected.

(Table 7)

5.2 Mission drift

At the outset, checking whether panel data estimations are really essential is very important; otherwise, variations among MFIs are so small that pooled regressions would be sufficient. F-tests of individual, time and joint effects confirm that all effects are significant at 1% level, thus rejecting the homogeneity assumption across MFIs and time. So, a pooled OLS regression would be inappropriate and we require panel data estimation methods (Wooldridge, 2002). Consequently, equation (4) is estimated using three panel methods: fixed-effects, random-effects, and first-difference. As presented in Table 8, results show that apart from the risk variable (PAR30) all other variables are significant and equally signed in all panel data estimations. Thus, it is quite logical to expect that the results from diverse panel data estimation methods are largely steady and consistent. Additionally, the high values of Hansen's J-statistic of over-identifying restrictions confirm that the instruments are not correlated with the error term. Hence, the instruments are relevant and the results we obtained are credible.

(Table 8)

The coefficients for the financial performance variable are generally negative and significant which indicate that social performance declines as financial performance of MFIs increases. Thus, the sampled MFIs are unable to ensure better depth of outreach (or social performance) as their financial performance improves. As a result, the concerns for mission drift seem valid. However, counterbalancing results also emerge. One of the efficiency measures, cost-per-borrower, has positive and highly significant coefficients. As discussed earlier, social performance scores are synthesised through positive loadings of average loan size variables and negative loadings of the female participation variable. Thus, a positive coefficient would mean that with increased average costs average loan size increases and female participation in credit programmes declines. So, when average costs increase it is quite natural for an MFI to try to replace small-sized loans with bigger ones in order to minimise average cost; although it raises the mission drift concern. This result is similar to those of Mersland and Strom (2010). Therefore, justifiably vulnerable and inefficient MFIs can increase average loan size for balancing the negative impacts of increased average costs. Cost-efficient MFIs, however, can extend loans to poorer, especially women, clients.

The exercise reveals a positive, but insignificant, relationship between risk and social performance across various models. The variable 'age' measures MFIs' propensity to change social performance over time, whose coefficients are negative all through and significant in three models. This indicates that depth of outreach declines as MFIs mature, all else being equal and given the definition of the social performance variable, this seems appropriate in regards to the mission drift concern. Again, the positive and highly significant coefficients for the size variable indicate that larger MFIs are not doing well in terms of social performance or reaching the very poor. Similar results in Table 7 confirm this finding. Regional variations, legal or profit standing and rating situation of MFIs were also controlled. However, coefficients for all of them were statistically insignificant.

6. Robustness analysis

Regression results in the analysis are robust to different variables, model specifications and data. Robustness of the results is mainly checked by re-estimating model (3) and model (4) employing different samples. As mentioned earlier, two other datasets have been used for this purpose, results of which are unreported in the interest of brevity. The first one is a panel dataset for 67 MFIs in Bangladesh for 5 years (from 2003 through 2007) and the second dataset contains a global sample of 426 MFIs in 81 countries where most of the observations are from the year 2007. Additionally, regressions with different combinations of control variables representing, for example, the scaling up situation, cost levels and risk scenarios of sampled MFIs were also run. For instance, we employed debt-equity ratio and write-off ratio as proxies for risk. Using this measure instead of or in addition to PAR30 did not bring any significant change and the results remained largely unperturbed. This leads to further credibility for our results.

7. Conclusions

Factor analysis helps us find out the common underlying factors in a group of similar variables. By definition, in factor analysis we are not required to ascribe any arbitrary weight to any variable as these weights are calculated from the correlation matrix of the variables. This is an obvious advantage which this study attempts to use so that similar variables can be combined into common factors. Various performance indicators commonly used for measuring MFI-performance are combined in this study. At the beginning it is similar in spirit to Weber and Ferro Luzzi (2007) who used factor analysis and cluster analysis to illustrate how these statistical tools can offer new insights in the context of MFIs' performance evaluation. However, this paper differs from their study mainly in that it employs different longitudinal cross-country datasets concerning different time periods with diverse model objectives—

ranging from determination of MFI-performance to addressing the concerns for mission drift. Another contribution of this exercise is that it utilizes country-specific data as suggested in previous studies.

To start with, two artificial indices portraying MFIs' social performance and financial performance have been constructed from six different MFI-performance variables using factor analysis. Then we look into possible determinants of these two performance indicators. As mentioned before, the mission drift issue finally boils down to a possible trade-off between or mutual exclusion of two of the common bottom-lines of MFIs—financial performance and social performance. Thus, in the final step the study explores whether the concerns for mission drift is credible by employing one of these artificial indices—social performance—as the outcome variable and another one—financial performance—as a control variable for further estimation.

The study finds that MFIs' scale of operation greatly influence their financial performance, both in terms of gross loan portfolio and number of clients (breadth of outreach). Deeper insight into this result suggests that larger loan portfolios significantly reduce delivery costs while small loans indeed cause costs per client to rise. MFIs are to reduce delivery costs for better financial performance as the results in the next step suggest that cost factors negatively affect financial performance. Therefore, along with increasing breadth of outreach, MFIs should focus more on increasing portfolio size to improve their financial performance. By doing so they will be able to minimize delivery costs significantly. Also there is a trade-off between risk factors and financial performance. So, if MFIs can avoid more risky loan portfolios their overall financial performance will improve. Results also suggest that large firms may not always be profitable; all the small enterprises may not be unprofitable either. So, contrary to common beliefs, scaling up may not always guarantee better financial performance.

Results also demonstrate that scale of operation, both in terms of gross loan portfolio and number of clients, plays a significant role in ensuring better social performance of MFIs. However, cost and efficiency measures may not affect social performance consistently. Sometimes, breadth of outreach is adversely affected by higher operational costs while at other times it may not be the case. Again, with an increased level of portfolio risk, social performance declines as MFIs will then switch to better-off clients for better repayments. So, concerns for mission drift are there. Also, in terms of size hypothesis such concerns are well founded since larger MFIs perform comparatively poorly in terms of social outcomes. Therefore, MFIs, especially who are socially-motivated, should take appropriate measures to that end. However, the MFI-age hypothesis does not support this trend as more experienced institutions are clearly doing well to achieve better social performance.

Thus, concerning the mission drift concerns, evidences in this exercise are fairly counterbalancing. Consequently, in line with Mersland and Strom (2010), it may be recommended that MFIs should try to replace small-sized loans with bigger ones when costs are increasing. For efficient MFIs this may raise the mission drift concern, but for relatively vulnerable and inefficient MFIs increasing average loan size to compensate the negative impacts of high average costs is a better way to follow. However, cost-efficient MFIs can continue extending loans to poorer clients, preferably to female clients. Following this way the concerns for mission drift can be reduced to a large extent.

This study is one of the first attempts to address the issue of mission drift in microfinance using the factor analysis. However, there are scopes for improvement. Self-reported data have been used in this exercise. Clearly, the sets of variables could be different from the ones used in this exercise. The sample size could have been larger too. So, rigorous studies based on richer, study-focused, especially country-specific, data could provide a clearer picture of factors determining MFI-performance or the scenario of trade-off between social and financial dimensions of MFI-performance. We hope to be able to address these issues in future studies.

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Table 1: Description of variables used in the factor analysis

Variable	Description	Values
Average loan size	(Total value of loans)/Number of credit clients	Continuous (in US$)
Average loan size (GNI-adjusted)	The same but adjusted by GNI per capita	Continuous (in %)
Women borrowers	Percentage of borrowers who are women	Continuous (in %)
Operational self-sufficiency	Operating revenue / (Financial expense + loan loss reserve provision + operating expense)	Continuous (in %)
Self-sufficiency index	Operational self-sufficiency / (1 + Operational self-sufficiency)	Continuous (in %)
Return on assets	Net operating income after taxes/Average total assets	Continuous (in %)

Table 2: Description of variables used in the regression analysis

Variable	Description
Gross loan portfolio	All outstanding principals due for all outstanding client loans.
Number of active borrowers	The number of current borrowers who have an outstanding loan
Cost per borrower	Operating expense/ Number of active borrowers, average
Ratio of operating expenses to gross loan portfolio	Operating Expense / Loan Portfolio, gross, average
Portfolio at risk (PAR30)	The fraction of loan portfolio that is overdue past 30 days or more; that is, PAR30 = Portfolio at risk/Gross loan portfolio
Write-off ratio	The ratio of loans that has been written-off and accepted as a loss; that is WOR = (Value of loans written-off) / (Loan portfolio, gross, average)
Size	Natural logarithm of total assets
Age	Number of years in MFI operation
East Asia and the Pacific (EAP)	A dummy = 1 if the MFI is in the EAP region and 0 otherwise
East Europe and Central Asia (EECA)	A dummy = 1 if the MFI is in the EECA region and 0 otherwise
Latin America and the Caribbean (LAC)	A dummy = 1 if the MFI is in the LAC region and 0 otherwise
Middle East and North Africa (MENA)	A dummy = 1 if the MFI is in the MENA region and 0 otherwise
South Asia (SA)	A dummy = 1 if the MFI is in the SA region and 0 otherwise
Sub-Saharan Africa (SSA)	A dummy = 1 if the MFI is in the SSA region and 0 otherwise
Non-profit NGO (NPNGO)	A dummy = 1 if the MFI's legal status is NPNGO and 0 otherwise
Rated	A dummy = 1 if the MFI is rated by any external rating agency and 0 otherwise

Table 3: Descriptive statistics of variables entering the analysis

Variable	Observation	Mean	Std. Dev.	Minimum	Maximum
Total assets	972	7.34e+07	4.03e+08	7058	6.45e+09
Age	1016	11.87	10.97	0	112
Active Borrowers	969	159445.40	668317.50	0	6707000
Loan portfolio	973	4.47e+07	2.04e+08	0	3.47e+09
Average loan	963	599.69	654.94	18	4561
Av. Loan (GNI-adj.)	958	62.45	78.06	2.25	604.50
Female loan clients	887	69.74	24.69	0	100
PAR30	927	3.81	5.44	0	64.25
Write-off ratio	832	1.55	2.53	-0.84	35.61
Op. Self-sufficiency	959	122.23	36.58	7.67	441.59
Self-sufficiency index	959	0.99	0.007	0.88	0.998
Return on assets	921	3.74	9.33	-64.54	97.04
Cost per borrower	903	118.40	104.63	0	662.80
Cost per $ (OELP ratio)	921	28.89	26.50	0	443.02
Rated	748	0.99	0.11	0	1
NPNGO	1017	0.38	0.49	0	1
EAP	1017	0.088	0.28	0	1
EECA	1017	0.168	0.374	0	1
LAC	1017	0.345	0.476	0	1
MENA	1017	0.071	0.257	0	1
SA	1017	0.097	0.297	0	1
SSA	1017	0.221	0.415	0	1

Sources: Author's own calculation from MIX data.

Table 4: Correlation matrix for 2005

	Av. loan	Av. loan (GNI-adj.)	Women Borrowers	OSS	Self-suff. index	ROA
Av. loan	1.0000					
Av. loan (GNI-adj.)	0.6591*	1.0000				
Women borrowers	-0.5319*	-0.5257*	1.0000			
OSS	0.1041	-0.0383	-0.1310	1.0000		
Self-suff. index	0.1334	-0.0334	-0.1417	0.9515*	1.0000	
ROA	-0.0231	-0.2563*	0.0452	0.8779*	0.9019*	1.0000

Sources: Author's own calculation from MIX data.

Table 5: Eigenvalues and proportion of variance explained

Year	Factor	Eigenvalue	Proportion	Cumulative
2000	Factor1	2.84446	0.4741	0.4741
	Factor2	2.10304	0.3505	0.8246
	Factor3	0.47650	0.0794	0.9040
	Factor4	0.32803	0.0547	0.9587
	Factor5	0.18213	0.0304	0.9890
	Factor6	0.06583	0.0110	1.0000
2001	Factor1	3.24915	0.5415	0.5415
	Factor2	1.81772	0.3030	0.8445
	Factor3	0.46363	0.0773	0.9218
	Factor4	0.32051	0.0534	0.9752
	Factor5	0.10769	0.0179	0.9931
	Factor6	0.04129	0.0069	1.0000
2002	Factor1	3.11518	0.5192	0.5192
	Factor2	1.89992	0.3167	0.8359
	Factor3	0.54393	0.0907	0.9265
	Factor4	0.31691	0.0528	0.9793
	Factor5	0.08773	0.0146	0.9939
	Factor6	0.03631	0.0061	1.0000
2003	Factor1	3.18145	0.5302	0.5302
	Factor2	1.92039	0.3201	0.8503
	Factor3	0.47693	0.0795	0.9298
	Factor4	0.30785	0.0513	0.9811
	Factor5	0.09445	0.0157	0.9968
	Factor6	0.01894	0.0032	1.0000
2004	Factor1	2.98287	0.4971	0.4971
	Factor2	2.05848	0.3431	0.8402
	Factor3	0.52451	0.0874	0.9276
	Factor4	0.30589	0.0510	0.9786
	Factor5	0.09562	0.0159	0.9946
	Factor6	0.03263	0.0054	1.0000
2005	Factor1	2.84298	0.4738	0.4738
	Factor2	2.19376	0.3656	0.8395
	Factor3	0.50464	0.0841	0.9236
	Factor4	0.32524	0.0542	0.9778
	Factor5	0.08964	0.0149	0.9927
	Factor6	0.04374	0.0073	1.0000
2006	Factor1	2.83485	0.4725	0.4725
	Factor2	2.26674	0.3778	0.8503
	Factor3	0.40360	0.0673	0.9175
	Factor4	0.33329	0.0555	0.9731
	Factor5	0.14022	0.0234	0.9965
	Factor6	0.02130	0.0035	1.0000
2007	Factor1	2.86774	0.4780	0.4780
	Factor2	2.18550	0.3642	0.8422
	Factor3	0.53342	0.0889	0.9311
	Factor4	0.28510	0.0475	0.9786
	Factor5	0.11929	0.0199	0.9985
	Factor6	0.00895	0.0015	1.0000

Sources: Author's own calculation from MIX data.

Table 6: Rotated factor loadings (oblique rotation) and unique variances

Year	Variable	Factor1	Factor2	Uniqueness
2000	lbbl	0.0022	0.8667	0.2485
	lbbgnil	-0.0278	0.8833	0.2242
	lwomborr	-0.0247	-0.8164	0.3285
	loss	0.9718	0.0127	0.0528
	lssi	0.9273	0.0650	0.1231
	ltroa	0.9667	-0.0765	0.0754
2001	lbbl	0.0735	0.8512	0.2388
	lbbgnil	-0.0604	0.8940	0.2241
	lwomborr	0.0012	-0.8253	0.3193
	oss	0.9583	0.0205	0.0714
	lssi	0.9769	-0.0047	0.0480
	ltroa	0.9871	-0.0122	0.0316
2002	lbbl	0.0188	0.8749	0.2278
	lbbgnil	-0.0490	0.8784	0.2429
	lwomborr	-0.0411	-0.7751	0.3850
	loss	0.9805	0.0123	0.0337
	lssi	0.9682	0.0653	0.0336
	ltroa	0.9808	-0.0775	0.0618
2003	lbbl	0.0753	0.8659	0.2178
	lbbgnil	0.0004	0.8731	0.2376
	lwomborr	0.0678	-0.8359	0.3199
	loss	0.9697	0.0398	0.0422
	lssi	0.9770	0.0583	0.0187
	ltroa	0.9822	-0.0834	0.0620
2004	lbbl	0.1421	0.8569	0.2174
	lbbgnil	-0.0719	0.8841	0.2279
	lwomborr	0.0587	-0.8000	0.3674
	loss	0.9688	0.0569	0.0454
	lssi	0.9748	0.0629	0.0316
	ltroa	0.9714	-0.1098	0.0690
2005	lbbl	0.0551	0.8681	0.2419
	lbbgnil	-0.1214	0.8787	0.2165
	lwomborr	-0.0800	-0.7987	0.3536
	loss	0.9699	0.0585	0.0541
	lssi	0.9796	0.0738	0.0327
	ltroa	0.9578	-0.1506	0.0645
2006	lbbl	0.0458	0.8802	0.2231
	lbbgnil	-0.1541	0.8715	0.2166
	lwomborr	-0.1192	-0.8450	0.2719
	loss	0.9719	0.0489	0.0530
	lssi	0.9844	0.0540	0.0281
	ltroa	0.9387	-0.1145	0.1057
2007	lbbl	0.0909	0.8923	0.1908
	lbbgnil	-0.1518	0.8735	0.2217
	lwomborr	-0.0753	-0.7833	0.3772
	loss	0.9767	0.0671	0.0378
	lssi	0.9844	0.0421	0.0267
	ltroa	0.9485	-0.1206	0.0926

Sources: Author's own calculation from MIX data.

Table 7: Determinants of MFI performance

	Financial performance			Social performance		
	SUR	**FGLS**	**OLS (P-W)**	**FGLS**	**OLS (P-W)**	**SUR**
GLP	0.736***	0.495***	0.559***	0.151**	0.218*	0.951***
	(0.135)	(0.108)	(0.167)	(0.051)	(0.090)	(0.129)
NAB	-0.328**	-0.225**	-0.214	-0.354***	-0.425***	-1.262***
	(0.124)	(0.070)	(0.110)	(0.040)	(0.056)	(0.118)
CPB	-0.505***	-0.453***	-0.413***	0.451***	0.336***	-0.475***
	(0.125)	(0.079)	(0.109)	(0.043)	(0.058)	(0.119)
OELP	0.173	-0.021	-0.035	-0.667***	-0.538***	0.177
	(0.112)	(0.054)	(0.086)	(0.030)	(0.069)	(0.107)
PAR	-0.032*	-0.036**	-0.032*	0.021***	0.009	0.059***
	(0.016)	(0.013)	(0.014)	(0.006)	(0.008)	(0.014)
WOR	-0.048***	-0.028**	-0.027**			
	(0.014)	(0.010)	(0.010)			
Size	-0.344***	-0.235**	-0.312**	0.093*	0.081	0.276**
	(0.095)	(0.087)	(0.110)	(0.043)	(0.070)	(0.091)
Age				-0.005	0.031	-0.233***
				(0.030)	(0.040)	(0.040)
EAP	-0.142	-0.245**	-0.188*	0.427***	0.287***	0.351***
	(0.075)	(0.085)	(0.089)	(0.062)	(0.055)	(0.071)
EECA	0.133*	-0.003	0.026	-0.017	-0.118*	0.053
	(0.053)	(0.055)	(0.072)	(0.056)	(0.056)	(0.054)
MENA	-0.098	-0.149	-0.130	0.111	0.148	-0.116
	(0.072)	(0.076)	(0.075)	(0.057)	(0.084)	(0.071)
SA	-0.584***	-0.810***	-0.710***	0.166*	0.040	0.165
	(0.095)	(0.093)	(0.147)	(0.074)	(0.066)	(0.092)
SSA	-0.047	-0.104*	-0.075	0.551***	0.470***	0.507***
	(0.051)	(0.048)	(0.069)	(0.035)	(0.038)	(0.049)
NGO	-0.126***	-0.195***	-0.175*	-0.331***	-0.515***	-0.057
	(0.038)	(0.043)	(0.074)	(0.034)	(0.068)	(0.038)
Rated	0.805***	0.701***	0.636			
	(0.152)	(0.146)	(0.534)			
Const.	-1.597**					-4.830***
	(0.589)					(0.555)
χ^2	328.89	763.16	2679.20	5445.79	3571.24	3129.21
R^2	0.40		0.54		0.86	0.86
N	493	489	493	768	769	493

All variables are in natural logs. GLP = Gross loan portfolio (this means scale of operation), NAB = Number of active borrowers (Breadth of outreach) , CPB = Cost per borrower, OELP = Operating expense to gross loan portfolio ratio, PAR = Portfolio-at-risk past 30 days, WOR = Write-off ratio, Size = Natural logarithm of total assets, Age = Number of years in microfinance operation, EAP = East Asia and the Pacific, EECA = Eastern Europe and Central Asia, MENA = Middle East and North Africa, SA = South Asia, SSA = Sub-Saharan Africa, NGO = Non- profit non-governmental organization, Rated = Whether rated by any external authority. SUR = Seemingly unrelated regressions with pooled data, FGLS = Panel data feasible generalized least squares model with panel-specific AR1 correlation, OLS (P-W) = OLS or Prais-Winsten models with panel-corrected standard errors; FGLS and OLS (P-W) have been used for HPAC (panel heteroskedasticity, panel autocorrelation, and contemporaneous correlation) SUR solution for contemporaneously correlated error terms.
Significance level: * = $p<0.05$, ** = $p<0.01$, *** = $p<0.001$.

Table 8: Trade-off between social performance and financial performance
Dependent variable: Social performance

	GMM-FD	GMM-FE	G2SLS	FE2SLS	EC2SLS
Fin. Perf.	1.179	-0.296	-0.261*	-0.291*	-0.177
	(1.229)	(0.183)	(0.122)	(0.132)	(0.113)
Size	0.098	0.200***	0.228***	0.210***	0.221***
	(0.119)	(0.043)	(0.033)	(0.037)	(0.033)
Age	-0.125	-0.253	-0.389**	-0.352*	-0.375**
	(0.649)	(0.261)	(0.126)	(0.160)	(0.124)
CPB	0.539*	0.363**	0.398***	0.382***	0.415***
	(0.264)	(0.138)	(0.045)	(0.049)	(0.044)
PAR30	0.043	0.008	0.015	0.011	0.021
	(0.037)	(0.021)	(0.015)	(0.015)	(0.014)
EAP			-0.190		-0.164
			(0.262)		(0.259)
EECA			0.331		0.303
			(0.198)		(0.196)
MENA			-0.410		-0.407
			(0.266)		(0.262)
SA			-0.403		-0.368
			(0.270)		(0.269)
SSA			0.195		0.197
			(0.178)		(0.177)
NP-NGO			-0.108		-0.119
			(0.143)		(0.142)
Rated			-0.066		-0.068
			(0.590)		(0.580)
Constant	0.058		-4.139***	-3.889***	-4.149***
	(0.070)		(0.840)	(0.702)	(0.826)
Hansen's J Statistics	0.7476	0.3057			
R-squared	-0.907	0.234	0.6036	0.4221	0.6119
N	283	370	373	373	373

* p<0.05, ** p<0.01, *** p<0.001; R-squared G2SLS = R^2-Overall, FE2SLS= R^2-Within and EC2SLS = R^2-Overall. All specifications were two-way error-component models containing time-effects. However, their results are not presented.

Figure 1: Scree plot of eigenvalues for 2003