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- An analysis of the drivers of the MFI ratings

by

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Abstract

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1. Introduction

During the last decade, several firms have specialised in conducting rating assessments of microfinance institutions (MFIs). Established rating agencies like Fitch and Standard and Poor's have also conducted MFI ratings (Fitch 2008). The purpose of rating reports is to present independent information that stakeholders like lenders, owners or managers can use to make informed decisions. Donors are particularly likely to consider external assessments important and to support the rating of MFIs. The first international rating fund offering co-funding for microfinance ratings was launched in 2001 by the Consultative Group to Assist the Poor (CGAP) and the Inter-American Development Bank (IDB). Following the close of this initial fund in 2008, two new initiatives were launched to co-finance and promote the use of ratings and assessments in the microfinance industry (see www.ratinginitiative.org and www.ratingfund2.org). Nevertheless, Hartarska (2005) reports that whether a firm is rated or not has no influence on Eastern European MFI performance. Moreover, Hartarska (2009) finds that only some rating agencies influence the actions of MFIs and that subsidised ratings do not help MFIs to raise more funds (Hartarska & Nadolnyak 2008). Thus, there is an obvious need for more information about microfinance ratings.

Mixmarket is a webpage (www.mixmarket.org) where MFIs can present their profiles to funders and other industry actors. Mixmarket stresses the importance of transparency and has established a diamond system in which the maximum score of 5 diamonds is only given to those MFIs that present an external rating report that supports the information provided to the MIX. Thus, for most MFIs, and especially for those in need of international funding, external ratings have become a necessity.

The recent financial crisis taught the global community a lesson about ratings. The high ratings for several financial instruments turned out to be inaccurate. Similar lessons can be found in the microfinance industry. For example, Microfinanza awarded the Afghanistan MFI Normicro a BB rating in 2006 and a BBB- rating in 2008. A triple B rating is considered a good rating in the microfinance industry and is considerably above the average, which in our dataset is approximately a B. One result of the good ratings was that several international funds, including the EU Bank for Reconstruction and Development (EBRD) and the US-based firm MicroCredit Enterprises, invested in Normicro (Microcapital Monitor March and April 2008; www.microcapital.org). From 2007 to 2008, Normicro more than doubled its international borrowing (audited statements for 2008 are available at www.mixmarket.org). A few months later, Normicro found itself in serious trouble because of severe internal fraud and mismanagement, which investigations confirmed had been going on for years. As a result, the major shareholder, Kolibri Kapital, has lost its whole investment, and the rest of the lenders are currently struggling to keep the MFI afloat and minimise their losses (Annual report Kolibri Kapital 2009, www.kolibrikapital.no).

In this study, we investigate the drivers of a good MFI rating. As expected, the findings indicate that firm size and profitability are positively related to MFI ratings, whereas there is a negative relationship between ratings and risk. Unexpectedly, we find that both efficiency and solvency are unrelated to the ratings by all but one of the analysed rating agencies. Furthermore, none of our analyses reveal a statistical relationship between social performance and ratings. To the best of our knowledge, this study is the first to use multivariate techniques in evaluating the drivers of MFI ratings. We present evidence that prior research that has only used bivariate statistical techniques to a limited degree has yielded hasty conclusions; it fails to recognise the simultaneous influence of correlated explanatory variables. In addition, and contrary to prior research, we investigate the possible influence of solvency on ratings, as this is one of the major explanatory variables for traditional credit ratings. We are also the first to provide evidence of possible differences between the rating agencies. Although some of the rating drivers are common to all of the agencies investigated, significant differences between the agencies do exist.

The rest of this paper proceeds as follows. Section 2 discusses relevant prior research on MFI ratings, presents the hypotheses to be tested, and introduces the research design. Section 3 presents the data sample, and Section 4 analyses the results of the empirical studies. In addition to the main tests, we also discuss a large number of robustness checks. Section 5 concludes.

2. Theoretical Background, Hypotheses, and Research Design

Public risk rating agencies have been in existence for decades, and names like Standard and Poor's, Fitch and Moody's are well known in business circles. These traditional rating services are exclusively concerned with repayment risk; the ratings signal the likelihood that a specific debt obligation will be paid on time. In principle, any corporation or organisation can be rated, including MFIs, but the number of MFIs with credit ratings is still small (Gutierrez-Nieto and Serrano-Cinka 2007). However, another type of rating is common in the microfinance industry: so-called performance assessment ratings[1]. These ratings should not be confused with traditional credit risk ratings. Whereas such ratings measure the likelihood that a particular public or private debt issue will be re-paid in full and on time, performance assessment ratings measure a combination of creditworthiness, trustworthiness and excellence in microfinance (www.ratinginitiative.org). Thus, performance assessment ratings are supposedly much more extensive than pure credit risk ratings in terms of the information that they provide.

Sinha (2002) states that many MFI operations are a "black box" and that this creates questions about their performance. As a result, the need for performance assessments is urgent. Reille, Sananikone and Helms (2002) provide a thorough description of the assessment methodologies used with microfinance institutions. They state that performance assessment reports seek to answer the question "Is this a good organisation?" rather than the question "How likely am I to be repaid in full and on time?" The assessments may function as

[1] Lately, social ratings have also begun to be offered by MFI raters. In this paper, we focus fully on performance assessment ratings, also called global risk assessments by some.

management tools, but perhaps more importantly, such assessments are supposedly used by donors and investors making decisions about whether to finance a particular MFI. Rating agencies may take into account a number of considerations when making performance assessments, including but not limited to management, capital adequacy, asset quality, costs and rates of return, growth prospects, efficiency, risk, organisational considerations, and social performance. The list of qualities considered by the agencies is long and may differ from agency to agency. Thus, many stakeholders at MFIs may find it difficult to determine what performance assessments really indicate and how to interpret ratings.

As previously illustrated, there is a need for information on what drives the rating results included in performance assessment reports. Obviously, if investors use ratings as a basis for funding, they need a clear understanding of the information that a particular rating conveys. If the rating methodologies differ for different agencies, investors need to better understand what drives the results presented by each agency. Moreover, it is important for MFI management teams to know what drives ratings so that they can improve future ratings.

Hartarska (2005 and 2009) and Hartarska and Nydolnyak (2008) study whether rated MFIs perform better and whether they have better access to funding than do non-rated MFIs. In her studies, Hartarska does not consider what factors drive rating grades. However, Gutierrez-Nieto and Serrano-Cinka (2007) do study this question, analysing the influence of five aspects of MFIs on the ratings awarded. These researchers study how ratings relate to MFI size, profitability, efficiency, risk and social performance. As the authors expect, the study shows that larger, more profitable, more efficient and less risky MFIs achieve better ratings. However, the authors are unable to identify a statistical relationship between social performance and ratings. An obvious weakness of the study by Gutierrez-Nieto and Serrano-

Cinka (2007) is that they analyse only one agency (*Planet Rating*). As demonstrated by Hartarska and Nadolnyak (2008) and Hartarska (2009), the impact of ratings differs with the rating agency, and this creates a need for more knowledge regarding possible differences between drivers of ratings for different agencies. Furthermore, Gutierrez-Nieto and Serrano-Cinka (2007) only use bivariate statistical techniques, evaluating one explanatory variable at a time. Thus, their analysis fails to determine how the explanatory variables are related. For instance, if one of the explanatory variables is statistically related to another explanatory variable but not to the rating, the bivariate analysis may erroneously suggest a statistical relationship between the variable and the rating even when none exists.

In this study, we expand on the Gutierrez-Nieto and Serrano-Cinka (2007) study. First, we perform a multivariate analysis to assess the influence of all of the explanatory variables simultaneously. Secondly, we use a much larger sample. Thirdly, we include reports from several different rating agencies, and fourthly, we examine if solvency is related to MFI ratings. The risk variables examined by Gutierrez-Nieto and Serrano-Cinka (2007) are short term and do not capture the long-term risk typically evaluated by solvency measures. Solvency is among the main drivers of traditional risk ratings (Belkaoui 1980; Fitch 2008; Kaplan and Urwitz 1979), and we expect this measure to also influence MFI ratings. Our hypotheses regarding the rest of the test variables are based on the findings of Gutierrez-Nieto and Serrano-Cinka (2007). The hypotheses are summarised in Table 1.

[Insert Table 1 here]

As indicated in Table 1, we expect that larger MFIs will be better able to meet their commitments and fulfill their goals; hence, we hypothesise a positive relationship between

MFI size and the ratings assigned. The hypotheses regarding profitability, efficiency, risk, and solvency are fairly intuitive.

MFIs operate with a double bottom line and should work to ensure financial returns alongside social returns (Morduch 1999). One should therefore expect that social returns influence rating grades. From a purely financial viewpoint, one might argue that social performance could have a negative impact on ratings because there is a trade-off between social and financial results (Mersland and Strøm 2010; Hermes *et al.* forthcoming). On the other hand, if the main objective of determining ratings is to conduct a comprehensive investigation of MFIs' ability to meet their many goals simultaneously, then one might argue that social performance should indeed be positively related to ratings. After all, one should expect that donors will only be willing to support an MFI if they are assured of its achieving good social results (Hartarska and Nadolnyak 2008). This expectation is supported by Gutierrez-Nieto and Serrano-Cinka (2010), who find that social performance measures such as outreach affect perceptions of MFI quality, which is an important driver of funder loyalty in their study. Furthermore, there are also several empirical issues related to how social performance should be measured, and we will return to these issues in the next section.

We begin our empirical study with a correlation analysis similar to that of Gutierrez-Nieto and Serrano-Cinka (2007). We then use multivariate analysis to analyse the simultaneous influence of the variables on the ratings. Solvency is excluded from the initial regressions so that the findings can be compared with those of Gutierrez-Nieto and Serrano-Cinka (2007). Thus, the following regression is run on the pooled sample:

(1) $$RATE = \beta_0 + \beta_1 SIZE + \beta_2 PROF + \beta_3 EFF + \beta_4 Risk + \beta_5 SocPer + \varepsilon$$

where *SIZE* is MFI size, *PROF* is a measure of MFI profitability, *EFF* is a measure of MFI efficiency, *Risk* is a measure of MFI risk, and *SocPer* is a measure of MFI social performance. We drop subscripts *i* and *t* for simplicity.

Regression (1) analyses the multivariate relationship of the explanatory variables to MFI ratings and constitutes our starting point for the analysis. However, specification (1) implicitly assumes that there are no other effects on MFI ratings than the influence of the test variables. To control for other possible effects, such as the influence of geographical location or economic conditions, (1) is extended with CONTROL, which is a vector of control variables. The CONTROL vector consists of both firm controls and context controls. The firm control variables include MFI type, MFI age, and rating agency, whereas the context control variables consist of GDP growth, geographical region, the Human Development Index (HDI) and the year the rating is conducted.

(2) $$RATE = \beta_0 + \beta_1 SIZE + \beta_2 PROF + \beta_3 EFF + \beta_4 Risk + \beta_5 SocPer + \beta_7 CONTROL + \varepsilon$$

The third regression adds a proxy for solvency (*SOLV*):

(3)

$$RATE = \beta_0 + \beta_1 SIZE + \beta_2 PROF + \beta_3 EFF + \beta_4 Risk + \beta_5 SocPer + \beta_6 SOLV + \beta_7 CONTROL + \varepsilon$$

The analysis is repeated with sub-samples split according to the rating agency. One regression is run for each agency. We are then able to identify possible differences between the agencies.

3. Data Sample and Variable Definitions

Mitra, Ranjan, and Negi (2008) indicate that there are around 16 rating agencies that are active in microfinance. This study includes performance assessment reports made by the five leading microfinance rating agencies. These agencies are the US-based *MicroRate*, the Italian-based *Microfinanza,* the French-based *Planet Rating* (the only agency studied by Gutierrez-Nieto and Serrano-Cinka 2007) and the two Indian-based agencies *Crisil* and *M-Cril*. Even if an agency argues that its methodology is different from that of other agencies (Mitra *et al.* 2008), the core information used in this study consists of standard indicators that are calculated alike across the industry. All agencies consider themselves as operating worldwide. However, the Indian-based agencies are more active in Asia, whereas the others are more active in Africa, Latin America and Eastern Europe. The rating reports that form the dataset are subsidised by Ratingfund 1 and were downloaded from www.ratingfund2.org. The observations are from the period from 2001 to 2008. The sample consists of 324 firm-year observations, but because there were missing observations for some of the explanatory variables, the total number of observations in the multivariate analysis is 304 or 302 depending on whether control variables are included in the analyses.

The five rating agencies use different rating scales with different combinations of letters making up the final ratings. Because they all use unique scale systems, all rating scales have been mathematically converted into a uniform scale so that we can analyse the drivers of the ratings for the pooled sample. RATE is the transformed grade, and it takes values between 0 and 1. The higher the number is, the better the rating. Figure 1 shows the distribution of MFIs according to their transformed rating scale. As illustrated in Figure 1, the transformed rating scores are relatively normally distributed around the average of 0.4321 (approximately a B rating). However, a rather large proportion of MFIs (26 observations) were assigned a rather poor grade (a grade of D or E depending on the agency), making the distribution somewhat skewed to the left.

[Insert Figure 1 about here]

We use the log of total assets, *LN(ASSETS)*, as our primary size variable in the regressions. Profitability is measured through return on assets, *ROA*, and operating expenses relative to total loan portfolio, *OEX_PORTF*, form the efficiency measure. Risk is measured as the portfolio at risk > 30, *PAR30*.[2] The social performance indicator is the average outstanding loan amount adjusted for GDP in the countries where the MFIs are situated, *AVG_LOAN_PPP*. These listed explanatory variables are the same as those used in Gutierrez-Nieto and Serrano-Cinka (2007). We add the debt to equity ratio, DEBT/EQUITY, as our measure of solvency. We will refer to this main regression specification as *Model 1*:

Model 1:
$$\begin{aligned}&RATE = \beta_0 + \beta_1 LN(ASSETS) + \beta_2 ROA + \beta_3 OEX\_PORTF + \beta_4 PAR30\\&+ \beta_5 AVG\_LOAN\_PPP + \beta_6 DEBT/EQUITY + \beta_7 CONTROL + \varepsilon\end{aligned}$$

Note that several different proxy variables could have been chosen. Thus, we study the robustness of the conclusions by replacing the chosen explanatory variables with various alternatives.

Table 2 displays the descriptive statistics for the above-listed variables. Most of the variables appear to have rather symmetric distributions, as their medians are close to their means. The

[2] Portfolio at risk > 30 refers to the oustanding balance of loans more than 30 days past due divided by the average outstanding gross loan portfolio.

average rating grade is 0.4321[3]. The grades range from 0.045 (the worse grade) to 0.9 (the best grade). The mean *LN(ASSETS)* is 15.1416, which corresponds to 3.8 million USD. The profitability of the sample is relatively high; the return on assets is 3.2% on average, which is higher than typically reported in the microfinance industry (Microbanking-Bulletin 2007) . The MFIs have operating expenses equal to 27.7% of their total loan portfolio average, illustrating the high cost associated with small loans. The mean for portfolio at risk is 5.83% of the gross loan portfolio. The average GDP-adjusted loan size is 1.137 USD, and the mean debt-to-equity ratio is relatively high at 6.82.

[Insert Table 2 about here]

4. Empirical Analysis

We begin our analysis of the factors explaining MFI ratings by evaluating the ratings' pairwise correlation coefficients using the explanatory variables. This analysis is comparable to the bivariate analyses of Gutierrez-Nieto and Serrano-Cinka (2007). Table 3 presents the standard Pearson correlations (below the diagonal) and non-parametric Spearman correlations (above the diagonal). The correlation matrix shows that size (*LN(ASSETS)*) and profitability (*ROA*) are positively related to ratings, whereas cost efficiency (*OEX_PORTF*) and risk (*PAR30*) are negatively associated with ratings. This means that the larger, more profitable, more efficient, and less risky MFIs tend to have the best ratings on average. The correlation matrix suggests that social performance (*AVG_LOAN_PPP*) is unrelated to ratings. The findings hold for both the Pearson and the Spearman correlations; in general, the Spearman correlations are close to the Pearson correlations for the variables studied. Overall, the findings of the bivariate analysis in Table 3 are in accordance with the previous findings by

[3] The number corresponds to approximately an A- for *Microrate*, a B for *Planet*, a BBB for *Microfinanza*, a rating of MFR4 for *CRISIL*, and an A for *M-CRIL*.

Gutierrez-Nieto and Serrano-Cinka (2007). However, to draw conclusions based on simple correlations is premature; the joint effect of all of the explanatory variables and their interrelation are disregarded in this analysis (although several of the explanatory variables have significant correlation coefficients, as reported in Table 3). Thus, we use a multivariate setting to analyse these statistical associations via regression analysis, as outlined in Section 2. Table 4 reports the findings.

[Insert Tables 3 and 4 about here]

Table 4 first presents the results of a simplified regression analysis. The control variables are left out of the first regression. Furthermore, our proxy for solvency, *DEBT/EQUITY*, is excluded from this analysis so that we can compare our results with those of Gutierrez-Nieto and Serrano-Cinka (2007). The second regression analysis includes the control variables, whereas the third presents the results of *Model 1* including solvency. Because the results of the three regressions are very similar, we focus our analysis on the results of the most comprehensive analysis (the two rightmost columns).

Table 4 shows that MFI size is significantly positively related to MFI ratings, just as the correlation analysis suggested.[4] The preliminary findings are also confirmed for profitability; return on assets is significantly associated with ratings. The more profitable the MFI, the higher its rating. Furthermore, cost efficiency remains negatively associated with ratings; the lower the operating expenses, the better the MFI rating. Also as hypothesised, risk is negatively related to ratings. However, GDP-adjusted average loan is an insignificant explanatory variable in all regressions. This means that according to our proxy variable, social

[4] We apply the term *significant* when the significance level as measured by the p-value is below 0.05 using a two sided test.

performance does not influence MFI ratings. None of these conclusions change when the control variables are included. Note that MFIs situated in countries with a high human development index (HDI) appear to have better ratings than others. Moreover, somewhat surprisingly, the ratings are negatively related to MFI age. This latter result suggests that relatively old MFIs have a lower rating than do "new" ones, which should motivate researchers to explore life cycle issues for MFIs. Finally, Table 4 presents evidence that solvency is positively related to ratings. Although not shown in prior research, these results appear logical and in accordance with the proposed hypotheses. The explanatory power of *Model 1* is high; an adjusted R^2 of more than 50% suggests that our explanatory variables capture the drivers of rating grades quite well.

All regression results are tested for the effect of possible outliers (not tabulated). First, the analyses are repeated using robust regressions. The first step in a robust regression is to conduct an initial screening based on Cook's distance (the value must be > 1) to eliminate gross outliers before calculating the starting values. Then, we perform Huber iterations and biweight iterations. This alternative test yields the same results as the main analysis. As a second robustness check, we re-run the regressions using a trimmed sample. The 1^{st} and 99^{th} percentiles for the dependent variable and the six explanatory variables are deleted. The results are very similar to those of the main analysis. However, the significance levels of efficiency and solvency are decreased, and these variables are now insignificantly related to rating grades.

When assigning a rating grade to an MFI, the rater may not only consider current performance but also analyse historic performance (a factor that is not considered in Gutierrez-Nieto and Serrano-Cinka 2007). To test this possibility, we can re-run the regressions using lagged values of the explanatory variables (not tabulated). This alternative test does not change the results in terms of size, profitability, risk, or social performance. However, efficiency and solvency are no longer significant explanatory variables. If the average of the current and lagged values of the explanatory variables is employed in the regression, efficiency remains insignificant. The adjusted R^2 increases to 62.99% in this regression, suggesting that historical observations for the explanatory variables are also relevant in explaining MFI ratings.[5] Note that this adjusted R^2 cannot be directly compared to the main analyses because the sample is not constant. The number of observations in the alternative regression drops to 259. Overall, the empirical analyses so far support the hypotheses of Table 1, but the results regarding efficiency and solvency appear to be somewhat weak.

Several alternative variables could have been chosen to proxy for size, profitability, efficiency, risk, social performance, and solvency. We have tested the robustness of our conclusions by investigating the influence of alternative proxies on the regression results. Table 5 reports the results. In our first alternative regression specification, the log of the loan portfolio (*LN(PORTF))* is used as the size proxy. The adjusted return on assets (*AROA*)[6] is the profitability proxy, whereas operating expenses divided by total assets (*OEX_ASSETS*) is the measure for efficiency. Risk is measured through portfolio write-offs (*WROFF*), and we use average loan size without adjusting for GDP to proxy for social performance (*AVG_LOAN*). Finally, current assets divided by short-term liabilities (*CA/SHD*) replace the debt-to-equity ratio as our proxy for solvency. *CA/SHD* is a more short-term solvency indicator than

[5] The regressions provide very similar results when lagged values of the explanatory variables are used to replace the current values because the explanatory variables are substantially auto-correlated. The correlations between the current and lagged values vary from 0.55 (*PAR30*) to 0.97 (*LN_ASSETS*).
[6] Because subsidies are common in microfinance, *AROA* can be used as a subsidy-adjusted indicator; it is calculated by rating agencies and often used as an alternative to the standard *ROA* measure.

DEBT/EQUITY and may also be regarded as a proxy for liquidity.[7] This regression specification is referred to as *Model 2*:

Model 2:
$$RATE = \beta_0 + \beta_1 LN(PORTF) + \beta_2 AROA + \beta_3 OEX\_ASSETS + \beta_4 WROFF + \beta_5 AVG\_LOAN + \beta_6 CA/SHD + \beta_7 CONTROL + \varepsilon$$

[Insert Table 5 about here]

This regression yields two results that are different from those of the main analysis in Table 4. Efficiency and solvency are no longer significant explanatory variables. Thus, the alternative proxy variables suggest that ratings are statistically unrelated to efficiency and solvency. We further test the robustness of our results by running a new regression with a third set of proxy variables. MFI size is now measured as the log of clients (*LN(CLIENTS)*), profitability as operational self-sustainability (*OSS*)[8], efficiency as the total number of loan clients divided by the total number of employees (personnel productivity = *PERS_PROD*), risk as risk coverage ratio (*RISK_COV*)[9], social performance as the percentage of female clients (*WOM_PERC*), and solvency as the total loan portfolio divided by total assets (*PORTF/ASSETS*). Thus, *Model 3* is specified as follows:

Model 3:
$$RATE = \beta_0 + \beta_1 LN(CLIENTS) + \beta_2 OSS + \beta_3 PERS\_PROD + \beta_4 RISK\_COV + \beta_5 WOM\_PERC + \beta_6 PORTF/ASSETS + \beta_7 CONTROL + \varepsilon$$

[7] Because *CA/SHD* is a relatively short-term solvency measure, it can also be viewed as a proxy for short-term risk and may thus capture the same information content as our risk proxies. The correlation coefficient of *CA/SHD* and *PAR30* is 0.02, and that of *CA/SHD* and *WROFF* is 0.14. Hence, the information content of *CA/SHD* appears to be different from that of our risk proxies.

[8] OSS is an indicator that shows whether the MFI covers its finance, operating and loan loss costs using its operating income.

[9] The risk coverage ratio measures the share of the loans that are 30 days past due that is covered by the default provisions in the MFI's financial statements.

Once again, the results of the main analysis indicating that efficiency and solvency are related to MFI ratings seem questionable. The two proxy variables are statistically insignificant, suggesting that the relation between efficiency, solvency, and ratings is weak. On the other hand, the results for social performance are very robust; all proxies of social performance, including female client targeting, appear to be (totally) unrelated to ratings. It should also be noted, however, that in the two latter regressions, missing observations for some of the alternative proxies leads to a drop in the total number of observations.

Numerous combinations of the variables in models 1-3 would have been possible as part of the regression analysis. In fact, even more proxy variables could have been studied. Thus, we have conducted one additional, comprehensive robustness check. In this untabulated analysis, we replace the proxy variables of Model 1 with relevant alternatives one at a time. The analysis strengthens the previously stated conclusions; size and profitability appear to be significantly positively associated with MFI ratings, whereas risk appears to be significantly negatively associated with ratings. No statistical relation is observed between the ratings and the social performance measures. The analysis confirms that the findings from the previous regression analyses regarding the relationship between ratings and efficiency and between ratings and solvency are weak and sensitive to the proxy variables chosen. Our conclusions regarding efficiency and solvency are actually sensitive not only to the proxy variables selected for these explanatory variables but also to the proxy variables selected for the other explanatory variables. The results regarding efficiency illustrate the importance of analysing the explanatory variables in a multivariate setting; in correlation analyses and other bivariate analyses (compare Table 3 in this study and that of Gutierrez-Nieto and Serrano-Cinka 2007), efficiency proxies tend to be significantly related to ratings. However, in more advanced multivariate analyses, the strength of this statistical relationship can very much be questioned.

The findings indicating that the drivers of ratings are size, profitability, and risk demonstrate that MFI ratings may not be very different from traditional credit ratings. If this is the case, why call them something different? For instance, in the classic study by Pogue and Soldofsky (1969), in which the authors construct a prediction model for new credit ratings, the explanatory variables were the ratio of long-term debt to total assets, the ratio of net income to total assets, the coefficient of variation in earnings, total assets, and the amount of interest over the change in interest. In another classic study (Horrigan 1966), pure financial ratios such as working capital to total sales, net worth to total debt, and sales to net worth were the explanatory variables used. A recent study by Altman and Sabato (2007) confirms the importance of financial indicators to credit ratings; EBITDA, total interest expense, short-term debt, and book equity are the most important explanatory variables in their model. Hence, it appears that the drivers of performance assessment ratings for MFIs are very similar to the drivers of traditional ratings.[10]

We now conduct an agency-specific analysis to study possible differences in rating methodologies, which are reported to be important in Hartarska (2009) and Hartarska and Nadolnyak (2008). Model 1 is run using the following sub-samples: *MicroRate*, *Microfinanza, Planet Rating*, and *M-Cril*.[11] We do not report separate results for *Crisil* because the number of observations available for this agency is low.

[Insert Table 6 about here]

[10] Aquino (2010) provides a comprehensive literature review of the use of financial indicators in credit ratings.
[11] Model 2 and model 3 are not applied because the number of observations for each agency is low.

Table 6 shows that size is significantly positively related to MFI ratings for all agencies and that risk is significantly negatively related to ratings. The relation between profitability and ratings is positive for all agencies and significant for *Planet* and *Microfinanca*. Social performance has a very insignificant coefficient for all agencies. Two particularly interesting results emerge when efficiency and solvency are analysed. In the main analysis in Table 4, efficiency was significantly positively related to ratings. This was also the case when solvency was considered. Table 6 suggests that the results for efficiency are driven by *Planet*. The regression coefficient is significant for this agency but not for any of the other agencies. In fact, *OEX_PORTF* shows surprisingly low t-values for all agencies but *Planet*. If the analysis is repeated using a pooled sample without the *Planet* observations, the t-value of *OEX_PORTF* is only -0.43 and is not at all significant (not tabulated). Hence, it appears that *Planet* is the only agency that attaches any weight to efficiency in determining ratings. Comparable results are reported for solvency. *Microrate* is the only agency with a significant coefficient. Thus, the main results indicating that solvency is positively related to MFI ratings appear to be solely driven by the *Microrate* ratings. A regression without the *Microrate* observations confirms this; the t-value for solvency becomes only -1.17 (not tabulated). [12]

The explanatory power of the agency-specific regressions varies from 46.76% to 70.87%. These levels are comparable to those of classic studies of credit ratings. For instance, Kaplan and Urwitz (1979) reported an explanatory power of 71%, whereas Horrigan (1966) was able to correctly predict just over one half of the samples of bond ratings. Thus, our models appear to be well specified, capturing much of the information relevant in computing MFI ratings. The weighted average of the adjusted R^2 is 62.02%. This is higher than the adjusted R^2

[12] The results regarding efficiency and solvency were somewhat sensitive to the influence of outliers in the overall sample. If a robust regression is used with the *Planet* sample, the t-value of *OEX_PORTF* actually *increases*. Similarily, an increase in the t-value of *DEBT/EQUITY* is observed if a robust regression is used with the *Microrate* sample. Thus, the agency-specific results for efficiency and solvency do not appear to be driven by outliers.

indicated by the pooled regression (which was equal to 54.19%). This finding suggests that the rating methodology is not constant across agencies; agency-specific differences cause agency-specific regressions to perform better than pooled regressions. An analysis of the regression coefficients yields a similar conclusion; most explanatory variables are standardised, and their coefficients may thus be compared across the regressions. An analysis of the coefficient of the risk proxy *PAR30* is particularly instructive in this regard. All agency-specific regressions show significant coefficients for this variable. However, the size of the coefficient varies substantially from one agency to the next. In the *M-CRIL* sample, the regression coefficient for *PAR30* is -1.56, whereas it is only -0.20 when the *Planet* sample is used. Having noted that the t-value also is much higher in the *M-CRIL* sample than in the *Planet* sample, one might conclude that *M-CRIL* seems to attach far more weight to risk than does *Planet*. On the other hand, *M-CRIL* seems to put less emphasis on profitability than do the other agencies.

Based on the assumption that ratings may be dependant on older information rather than just on the current values of the explanatory variables, all regressions in Table 6 are re-run using explanatory variables that are lagged one year (not tabulated). Although the significance level of some of the variables is slightly lower than indicated in Table 6, none of the conclusions are affected. If the average of the current observations and the lagged values is instead employed for all explanatory variables, the results become identical to the ones reported in Table 6. However, in this latter specification, the adjusted R^2 increases slightly in the *Planet* sample (from 70.87% to 74.58%). In the other sub-samples, this change decreases the adjusted R^2. Although the levels of explanatory power of the various specifications cannot be directly compared (because there are slightly fewer observations when lagged values are used), these results does provide some indication that *Planet* attaches more weight to historical information than do the other agencies.[13]

Overall, our empirical results can be summarised as follows: MFI size and profitability affect performance assessment ratings positively, whereas the influence of risk is negative. Social performance is consistently unrelated to ratings. In general, neither efficiency nor solvency seems to be related to ratings. However, there is evidence of a positive influence of efficiency on the ratings in the *Planet* sample and of a positive influence of solvency on those in the *Microrate* sample.

5. Concluding Remarks

This study presents a comprehensive multivariate analysis of the relation between MFI ratings, performance assessment ratings or global risk assessments, and MFI size, profitability, efficiency, risk, social performance, and solvency. Several proxies for the explanatory variables are examined, and a large number of regressions are run. The findings of this study indicating that MFI size and profitability are positively related to MFI rankings and that risk is negatively related to ratings are as expected. However, the finding indicating that efficiency seems to be totally unrelated to MFI ratings for all agencies but one is surprising. Many may find it objectionable that a rating that is supposed to measure how well MFIs are functioning (i.e., the degree to which they fulfil their objectives) does not reflect MFI operational efficiency. This criticism is strengthened by the fact that a lack of efficiency is often considered a major challenge for MFIs (see, e.g., Sinha 2002; Fitch 2008). One

[13] We also analyse whether the ratings can be expressed as a function of the change in the explanatory variables, but we generally find that the ratings are statistically unrelated to the latest annual changes in size, profitability, risk, efficiency, social performance, and solvency. We do, however, find that the change in risk is significantly related to ratings in the *Microfinanza* sub-sample. The relationship is negative as expected; the larger the increase in risk as measured by *PAR30*, the lower the rating.

consequence of excluding efficiency from ratings may be that MFIs do not improve efficiency levels because a high degree of efficiency is not required for them to receive a good rating.

A typical MFI has multiple bottom-line objectives and is expected to deliver both financial and social results. If these ratings are supposed to be comprehensive in the sense that they reflect firms' ability to achieve *all* objectives, then performance assessment ratings should also be a function of social performance indicators. However, we are unable to discover any statistical relationship between a number of social performance indicators and ratings. This conclusion holds for all rating agencies studied. Prior research (Gutierrez-Nieto and Serrano-Cinka 2007) has also failed to identify such a relationship. Thus, performance assessment ratings seem not to live up to the Rating Fund's definition of ratings as "an opinion of the ability to deliver according to objectives."

Because microfinance ratings do not consider operational efficiency or social performance, they are very similar to traditional credit ratings. It thus seems timely for donors to ask whether subsidising specialised microfinance rating agencies makes sense. In the long term, it is probably better for MFIs to be mainstreamed into traditional rating agencies, at least as long as the specialised agencies do not provide additional value. Moreover, because the specialised agencies (all except for Microrate) do not consider solvency risk, traditional credit raters are probably better able to provide true risk ratings for MFIs. Alternatively, if specialised rating agencies are to prove that they serve an important function, they must develop a methodology that allows them to evaluate MFIs' overall ability to reach their goals and handle resources efficiently. In general, ratings may have fostered a higher degree of transparency in the microfinance industry, but the quality of the ratings is very much debatable and deserves more attention by industry stakeholders and researchers. It will be particularly important to determine whether MFI managers use rating information to improve operations.

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Figure 1: Rating Distribution

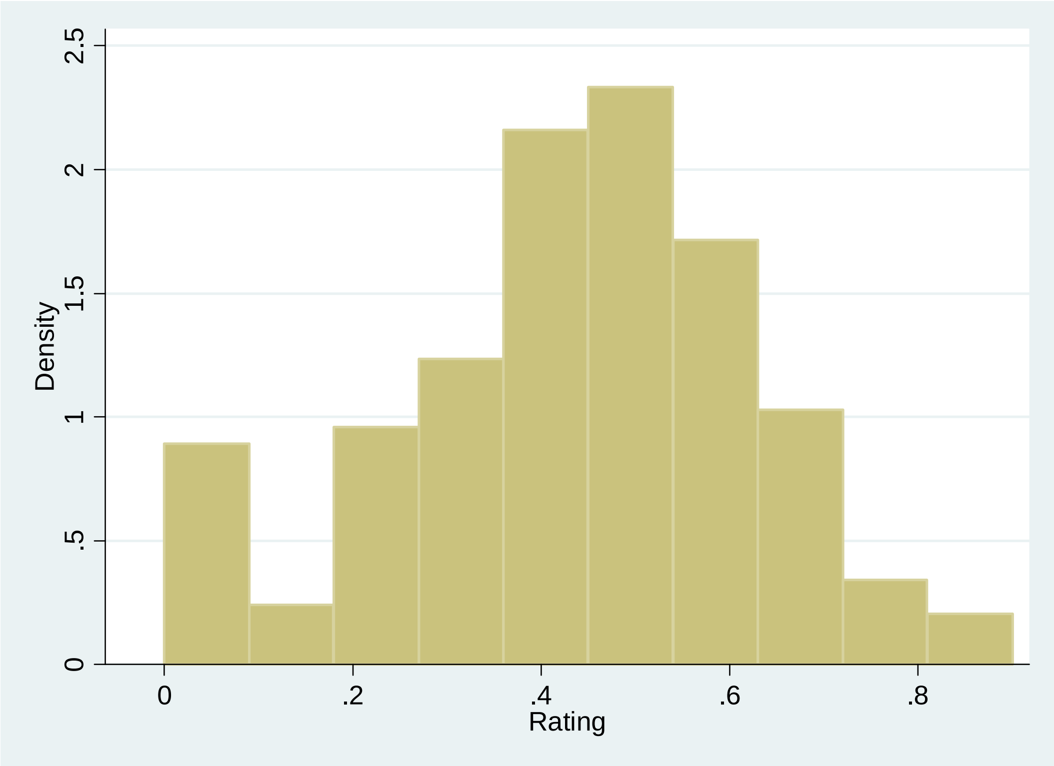

Figure 1 displays the distribution of the rating grades. There are 304 ratings in total, and the ratings have been determined by the US-based firm *MicroRate*, the Italian-based firm *Microfinanza*, the French-based firm *Planet Rating* and two Indian-based firms named *Crisil* and *M-Cril*. The five rating agencies use different ratings scales. The rating scales have been mathematically converted into a uniform scale with grades between 0 and 1; the higher the number is, the better the rating.

Table 1: Hypotheses

MFI Characteristic	**Hypothesis**
Size	MFI size is positively related to the rating assigned.
Profitability	MFI profitability is positively related to the rating assigned.
Efficiency	MFI efficiency is positively related to the rating assigned.
Risk	MFI risk is negatively related to the rating assigned.
Social performance	There is no relationship between the MFI's social performance and the rating assigned.
Solvency	MFI solvency is positively related to the rating assigned.

Table 2 presents the hypotheses used in the the empirical analyses.

Table 2: Descriptive Statistics

Variable	Mean	Q1	Median	Q3	St.Dev
RATE	0.4321	0.3000	0.4540	0.5600	0.1835
LN(ASSETS)	15.1416	14.2380	15.0931	15.9029	1.1713
ROA	0.0314	0.0045	0.0320	0.0734	0.0927
OEX_PORTF	0.2770	0.1540	0.2290	0.3535	0.1809
PAR30	0.0583	0.0100	0.0305	0.0670	0.0960
AVG_LOAN_PPP	1136.6070	218.4600	555.3400	1002.6600	3165.0140
DEBT/EQUITY	6.8159	0.6573	1.6624	3.5400	81.7700

Table 2 displays descriptive statistics for the MFI ratings and the 6 main explanatory variables: MFI size, profitability, efficiency, risk, social performance, and solvency. The five rating agencies that are analysed use different ratings scales. The rating scales have been mathematically converted into a uniform scale (*RATE*). The proxy variable for MFI size is the log of total assets, *LN(ASSETS)*; profitability is return on assets, *ROA*; efficiency is operating expenses relative to total loan portfolio, *OEX_PORTF*; risk is the relative proportion of the portfolio that is more than 30 days past due, termed portfolio at risk or *PAR30*; social performance is the average loan size adjusted for the GDP of the country where the MFI is located, *AVG_LOAN_PPP*; and solvency is debt divided by equity, *DEBT/EQUITY*. The observations cover 5 rating agencies: *Microrate*, *Planet*, *Microfinanza*, *CRISIL*, *M-CRIL*. The ratings cover the period 2001 to 2008.

Table 3: Correlations

Variable	RATE	LN(ASSETS)	ROA	OEX_PORTF	PAR30	AVG_LOAN_PPP	DEBT/EQUITY
RATE	**1.0000**	**0.4752**	**0.4691**	**-0.2202**	**-0.4290**	0.0335	-0.1075
LN(ASSETS)	**0.4741**	**1.0000**	**0.1697**	**-0.3075**	0.0229	**0.2951**	**0.1464**
ROA	**0.3236**	**0.1467**	**1.0000**	-0.0841	**-0.3040**	-0.0172	**-0.2092**
OEX_PORTF	**-0.2210**	**-0.2533**	**-0.1583**	**1.0000**	-0.0266	**-0.4659**	**-0.2437**
PAR30	**-0.3306**	-0.0102	**-0.1632**	-0.0959	**1.0000**	**0.2124**	0.0974
AVG_LOAN_PPP	0.0517	**0.1414**	0.0203	**-0.1818**	0.0495	**1.0000**	**0.1374**
DEBT/EQUITY	-0.0693	-0.0203	0.0157	-0.0442	-0.0412	-0.0125	**1.0000**

Table 3 presents Pearson (Spearman) correlation coefficients below (above) the diagonal for MFI rating (*RATE*), size (*LN(ASSETS)*), profitability (*ROA*), efficiency (*OEX_PORTF*), risk (*PAR30*), social performance (*AVG_LOAN_PPP*), and solvency (*DEBT/EQUITY*). All variables are defined in Table 2. Boldface denotes significance at a 5 % level with two-sided tests.

Table 4: Regression Analysis – Model 1

Variable	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value
LN(ASSETS)	**0.0650**	8.74	**0.0080**	9.17	**0.0734**	9.29
ROA	**0.3853**	4.14	**0.2786**	3.10	**0.2937**	3.30
OEX_PORTF	**-0.1191**	-2.43	**-0.1177**	-2.42	**-0.1236**	-2.57
PAR30	**-0.5827**	-6.57	**-0.4141**	-5.03	**-0.4180**	-5.14
AVG_LOAN_PPP	0.0000	-0.37	0.0000	-0.37	0.0000	-0.35
DEBT/EQUITY					**-0.0003**	-2.82
CONTROLS:						
GDP_GR			-0.0374	-1.27	-0.0378	-1.30
HDI			**0.1804**	2.59	**0.1758**	2.55
AGE_MFI			**-0.0032**	-2.87	**-0.0031**	-2.89
Indicator var:						
Year			Yes		Yes	
Region			Yes		Yes	
Type			Yes		Yes	
Agency			Yes		Yes	
Adj. R^2	37.54 %		53.03 %		54.19 %	
No. obs	304		302		302	

Table 4 displays the results of multivariate analyses of the influence of MFI size, profitability, efficiency, risk, social performance, and solvency on MFI ratings. The results of the following regressions are presented:

(1) $RATE = \beta_0 + \beta_1 LN(ASSETS) + \beta_2 ROA + \beta_3 OEX\_PORTF + \beta_4 PAR30 + \beta_5 AVG\_LOAN\_PPP + \varepsilon$

(2) $RATE = \beta_0 + \beta_1 LN(ASSETS) + \beta_2 ROA + \beta_3 OEX\_PORTF + \beta_4 PAR30 + \beta_5 AVG\_LOAN\_PPP + \beta_7 CONTROL + \varepsilon$

(3)
$RATE = \beta_0 + \beta_1 LN(ASSETS) + \beta_2 ROA + \beta_3 OEX\_PORTF + \beta_4 PAR30 + \beta_5 AVG\_LOAN\_PPP + \beta_6 DEBT / EQUITY + \beta_7 CONTROL + \varepsilon$

The test variables are defined in Table 2. *CONTROL* is a vector of control variables: *GDP_GR*, *HDI*, *AGE_MFI*, *Year*, *Region*, *Type* and *Agency*. *GDP_GR* is GDP growth, *HDI* is the human development index, *AGE_MFI* is the number of years since the institution began conducting microfinance activities, *Year* is a set of indicator variables for each year of observations (2000-2008), *Region* is a set of indicator variables for the MFIs' geographical locations (LA, Africa, MENA, EECA, and Asia), *Type* is a set of indicator variables for MFI type (bank, non-bank financial institution, NGO, cooperative/credit union, state bank, and other), and *Agency* is a set of indicator variables for the rating agencies (Microrate, Planet, Microfinanza, CRISIL, and M-CRIL). The table reports regression coefficients, t-values, explanatory power (Adj. R^2) and number of observations (No. obs). Boldface denotes significance at a 5 % level with two-sided tests.

Table 5: Alternative Regression Models

Panel A: Model 2

Variable	Coefficient	t-value
LN(PORTF)	**0.0886**	9.52
AROA	**0.2822**	4.09
OEX_ASSETS	0.0338	0.37
WROFF	**-0.9663**	-3.55
AVG_LOAN	0.0000	-0.43
CA/SHD	0.0053	1.48
CONTROLS:		
GDP_GR	0.3474	1.35
HDI	**0.1991**	1.99
AGE_MFI	**-0.0051**	-3.64
Indicator var:		
Year	Yes	
Region	Yes	
Type	Yes	
Agency	Yes	
Adj. R^2	56.97 %	
No. obs	184	

Panel B: Model 3

Variable	Coefficient	t-value
LN(CLIENTS)	**0.0743**	4.72
OSS	**0.1744**	3.74
PERS_PROD	-0.0006	-1.96
RISK_COV	0.0034	0.62
WOM_PERC	-0.0732	-0.78
PORTF/ASSE	0.1838	1.40
CONTROLS:		
GDP_GR	-0.5622	-1.43
HDI	0.0454	0.24
AGE_MFI	0.0000	-0.01
Indicator var:		
Year	Yes	
Region	Yes	
Type	Yes	
Agency	Yes	
Adj. R^2	52.29 %	
No. obs	78	

Table 5 displays the results of multivariate analyses of the influence of MFI size, profitability, efficiency, risk, social performance, and solvency on MFI ratings. Panels A and B reports the results of the following regressions, respectively:

$$RATE = \beta_0 + \beta_1 LN(PORTF) + \beta_2 AROA + \beta_3 OEX\_ASSETS + \beta_4 WROFF + \beta_5 AVG\_LOAN + \beta_6 CA/SHD + \beta_7 CONTROL + \varepsilon$$

$$RATE = \beta_0 + \beta_1 LN(CLIENTS) + \beta_2 OSS + \beta_3 PERS\_PROD + \beta_4 RISK\_COV + \beta_5 WOM\_PERC + \beta_6 PORTF/ASSETS + \beta_7 CONTROL + \varepsilon$$

LN(PORTF) is the log of the total loan portfolio, *AROA* is the adjusted return on assets, *OEX_ASSETS* is operating expenses divided by total assets, *WROFF* is total write-offs, *AVG_LOAN* is average loan size, *CA/SHD* is current assets divided by short-term liabilities, *LN(CLIENTS)* is the log of total clients, *OSS* is operational self-sustainability, *PERS_PROD* is the number of loan clients divided by the number of employees, *RISK_COV* is the risk coverage ratio, *WOM_PERC* is the percentage of female customers, and *PORTF/ASSETS* is the loan portfolio divided by assets. *CONTROL* is defined in Table 4. The table reports the regression coefficients, t-values, explanatory power (Adj. R^2) and number of observations (No. obs). Boldface denotes significance at a 5 % level with two-sided tests.

Table 6: Agency-Specific Analyses

	MICRORATE		PLANET		MICROFINANCA		M-CRIL	
Variable	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value
LN(ASSETS)	**0.0669**	2.58	**0.0937**	7.34	**0.0577**	4.79	**0.0737**	3.53
ROA	0.7316	1.88	**0.7097**	4.33	**0.7667**	3.95	0.1796	1.22
OEX_PORTF	-0.1376	-0.86	**-0.1853**	-2.96	-0.0493	-0.50	-0.1088	-0.56
PAR30	**-0.7129**	-2.71	**-0.2012**	-2.00	**-0.8557**	-4.40	**-1.5584**	-3.05
AVG_LOAN_PPP	0.0000	-0.66	0.0000	-0.07	0.0000	-0.15	0.0000	-0.69
DEBT/EQUITY	**-0.0029**	-4.99	-0.0005	-0.62	-0.0015	-1.40	-0.0001	-1.36
CONTROLS:								
GDP_GR	0.2397	0.17	-0.0208	-0.70	0.2977	1.15	0.1265	0.22
HDI	-0.0216	-0.11	**0.3572**	3.10	-0.0286	-0.23	**0.8699**	2.28
AGE_MFI	0.0005	0.09	**-0.0053**	-2.77	0.0019	1.01	-0.0028	-1.35
Indicator var:								
Year	Yes		Yes		Yes		Yes	
Region	Yes		Yes		Yes		Yes	
Type	Yes		Yes		Yes		Yes	
Adj. R^2	46.76 %		70.87 %		64.59 %		51.25 %	
No. obs	55		120		80		40	

Table 7 displays the results of multivariate analyses of the influence of MFI size, profitability, efficiency, risk, social performance, and solvency on MFI ratings from the agencies *Microrate*, *Planet*, *Microfinanza*, and *M-CRIL*. The results of the following regression are presented per agency:

$$RATE = \beta_0 + \beta_1 LN(ASSETS) + \beta_2 ROA + \beta_3 OEX\_PORTF + \beta_4 PAR30 + \beta_5 AVG\_LOAN\_PPP + \beta_6 DEBT/EQUITY + \beta_7 CONTROL + \varepsilon$$

The variables are defined in Table 4. The table reports regression coefficients, t-values, explanatory power (Adj. R^2) and number of observations (No. obs). Boldface denotes significance at a 5 % level with two-sided tests.