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An Analysis of the Drivers of Microfinance Rating Assessments

Leif Atle Beisland[1] and Roy Mersland[1]

Abstract

Rating assessments of microfinance institutions (MFIs) are claimed to measure a combination of creditworthiness, trustworthiness, and excellence in microfinance. Using a global data set covering reports from 304 microfinance institutions, this study suggests that these ratings are mainly driven by size, profitability, and risk. The overall results suggest that microfinance ratings convey information similar to that communicated by traditional credit ratings. All results are remarkably consistent across rating agencies. The determinants of the rating grades are found to be the same in all subsamples.

Keywords

microfinance, MFI, rating, performance, assessment

Introduction

Since Muhammad Yunus and Grameen Bank received the Nobel Peace Prize in 2006, microfinance has become a universal and well-known concept. Generally, the attention has been positive, and the potential for microfinance to lift poor people out of poverty has been highlighted. Similarly, microfinance is a new international investment opportunity, as foreign investments in microfinance have quadrupled over the past 4 years and were calculated to be valued at US$13 billion at the end of 2010 (Reille, Forster, & Rozas, 2011).

Recently, however, microfinance has come under public and media attack. It is now being asked whether microfinance institutions (MFIs) actually help bring poor people out of poverty, charge overly high lending rates, and practice collection methods that

[1]University of Agder, Kristiansand, Norway

Corresponding Author:
Roy Mersland, University of Agder, Gimlemoen, Kristiansand 4600, Norway
Email: roy.mersland@uia.no

are too heavy handed. Particularly, the microcredit crisis after the microfinance-induced suicides in 2010 in the Southern Indian state of Andhra Pradesh indicates that there are large differences between microfinance practices. As a consequence, microfinance stakeholders now search for independent information to assess the quality of an MFI.

The increased need for independent MFI information has led several firms to offer specialized rating assessments of MFIs. These rating assessments are much wider than traditional credit ratings, as they claim to measure the MFIs' ability to reach their multiple sets of objectives (Reille, Sananikone, & Helms, 2002). The purpose of rating reports is to present independent information that stakeholders, such as lenders, donors, owners, or managers, can use to make informed decisions.

The first international rating fund offering cofunding 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 cofinance and promote the use of ratings and assessments in the microfinance industry (see http://www.ratinginitiative.org and http://www.ratingfund2.org). Nevertheless, Hartarska (2005) reports that whether an MFI is rated has no influence on Eastern European MFI performance. Moreover, Hartarska (2009) finds that only some rating agencies influence the actions of MFIs and that subsidized ratings do not help MFIs to raise more funds (Hartarska & Nadolnyak, 2008). Thus, there is an obvious need for more information about what actually constitutes the microfinance ratings.

Mixmarket is a webpage (http://www.mixmarket.org) where MFIs can present their profiles to funders and other industry actors. Mixmarket stresses transparency and has established a diamond system in which the maximum score of five 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, the Azerbaijan MFI Normicro was rewarded a BB rating in 2006 and a BBB rating in 2008. A BBB rating is considered a good rating in the microfinance industry and is considerably above the average, which in our data set is approximately a B. One result of good ratings was that several international funds, including the EU Bank for Reconstruction and Development (EBRD) and the U.S.-based firm MicroCredit Enterprises, invested in Normicro (Microcapital Monitor, 2008). From 2007 to 2008, Normicro more than doubled its international borrowing (audited statements for 2008 are available at http://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 minimize their losses (Annual Report Kolibri Kapital 2009, http://www.kolibrikapital.no).

In this study, we investigate the drivers of the MFI ratings. 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 our proxies for solvency are unrelated to the ratings, both in the pooled sample and in the agency-specific analyses. Furthermore, none of our analyses reveals a statistical relationship between social performance and ratings.

To the best of our knowledge, this study is the first to use multivariate techniques to evaluate the drivers of MFI ratings. 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. Even if all the agencies claim to have their own rating methodology the drivers influencing the rating appear remarkably consistent across all agencies.

The rest of this article proceeds as follows. The section titled Theoretical Background, Hypotheses, the section Research Design discusses relevant prior research on MFI ratings and presents the hypotheses to be tested, the section Data Sample and Variable Definitions presents the data sample, and the section Empirical Analysis analyzes the results of the empirical studies as well as a large number of robustness checks. The last section, Summary and Concluding Remarks, summarizes the findings and provides conclusions.

Theoretical Background, Hypotheses, and Research Design

Public risk-rating agencies have been in existence for decades, and names such as Standard and Poor's and Moody's are well known. 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 organization can be rated, including MFIs, but the number of MFIs with credit ratings is still small (Gutiérrez-Nieto & Serrano-Cinca, 2007). However, another type of rating is common in the microfinance industry: so-called performance assessment ratings. These ratings should not be confused with traditional credit-risk ratings because, in addition to creditworthiness, they measure issues such as trustworthiness and excellence in microfinance (http://www.ratinginitiative.org). Thus, performance assessment ratings are supposedly much more extensive than pure credit-risk ratings.

Sinha (2002) states that many MFI operations are a "black box" and that this creates questions about their performance. Reille et al. (2002) provide a thorough description of the assessment methodologies used with MFIs. They state that performance assessment reports seek to answer the question, "Is this a good organization?," rather than the question, "How likely am I to be repaid in full and on time?" The assessments may function as management tools, but more important, such assessments are 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, organizational considerations, and social performance.[1]

What exactly drives the rating result provided in the microfinance rating 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 information differs across 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.

As far as we know only Gutiérrez-Nieto and Serrano-Cinca (2007) have studied rigorously what factors drive the microfinance rating grades. They analyze five aspects of MFIs on the ratings awarded, namely, 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. It should be noted, however, that Gutiérrez-Nieto and Serrano-Cinca analyze only one agency (*Planet Rating*). As demonstrated by Hartarska and Nadolnyak (2007, 2008), 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, Gutiérrez-Nieto and Serrano-Cinca, because of a relatively small sample, 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 Gutiérrez-Nieto and Serrano-Cinca (2007) study. First, we perform a multivariate analysis to assess the influence of all of the explanatory variables simultaneously. Second, we use a much larger sample. Third, we include reports from several different rating agencies, and fourth, we examine whether solvency is related to MFI ratings. Solvency is among the main drivers of traditional risk ratings (Fitch Ratings, 2008; Kaplan & 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 Gutiérrez-Nieto and Serrano-Cinca. The hypotheses are summarized in Table 1.

As indicated in Table 1, we hypothesize a positive relationship between MFI size and the ratings assigned. Likewise, the hypotheses regarding profitability, efficiency, risk, and solvency are fairly intuitive. A more complex issue, however, is the relationship between the MFI rating and social performance.

MFIs operate with a double bottom line and should work to ensure financial returns alongside social returns (Morduch, 1999). Heille et al. (2002) state the MFI ratings are "holistic evaluations of MFIs' financial and overall performance" (p. 10), whereas Gutiérrez-Nieto and Serrano-Cinca (2007) contend that "MFIs have to submit themselves

Table 1. Hypotheses

MFI (Microfinance Institution) 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.

Note: The table presents the hypotheses used in the empirical analyses.

to performance assessments taking into account their dual nature: financial and social" (p. 440). One should, therefore, expect that social returns influence rating grades. The direction of a possible relationship is nonetheless not obvious because there is a trade-off between financial and social returns (Hermes, Lensink, & Meesters, 2011; Mersland & Strøm, 2010). Thus, although social performance is a vital objective for most MFIs and although the MFI ratings are supposed to measure "excellence in microfinance" on an overall level, few of the rating agencies explicitly state that social performance is a determinant of their rating grade. This can explain the findings of Gutiérrez-Nieto and Serrano-Cinca that social performance is statistically unrelated to the grades. It can also explain why some rating agencies have begun to offer pure social ratings. We regard the question of whether the rating grades actually reflect the double bottom line of MFIs to be important, and we include an analysis of social performance to test whether the conclusions of Gutiérrez-Nieto and Serrano-Cinca withstand a multivariate test methodology.

We begin our empirical study with a correlation analysis similar to that of Gutiérrez-Nieto and Serrano-Cinca (2007). We then use multivariate analysis to analyze the simultaneous influence of the variables on the ratings. The following regression is run on the pooled sample:

$$RATE = \beta_0 + \beta_1\,SIZE + \beta_2\,PROF + \beta_3\,EFF + \beta_4\,Risk + \beta_5\,SocPer + \beta_6\,SOLV + \beta_7\,CONTROL + \varepsilon \tag{1}$$

where *RATE* is the rating grade assigned by the rating agency to the MFI, *SIZE* is MFI size, *PROF* is a measure of profitability, *EFF* is a measure of efficiency, *Risk* is a measure of MFI risk, *SocPer* is a measure of social performance, and *SOLV* is a measure of solvency. CONTROL 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 (gross domestic product) growth, geographical region, the Human Development Index (HDI), and the year the rating is conducted. We drop subscripts i and t for simplicity.

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

Data Sample and Variable Definitions

This study includes performance assessment reports made by the five leading microfinance rating agencies: the U.S.-based *MicroRate,* the Italy-based *Microfinanza,* the France-based *Planet Rating* (the only agency studied by Gutiérrez-Nieto & Serrano-Cinca, 2007) and the two India-based agencies, *CRISIL* and *M-CRIL*. Even if an agency argues that its methodology is different from that of other agencies (Mitra, Ranjan, & Negi, 2008), the core information used in this study consists of standard indicators that are calculated similarly across the industry. All agencies consider themselves to operate 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 data set are subsidized by Ratingfund 1 and were downloaded from the website, http://www.ratingfund2.org. The observations are for the period 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 scale systems, the different rating scales were easily converted mathematically into a uniform scale, *RATE*, which takes values between 0 and 1. The higher the number is, the better the rating. Specifically, the lowest grade of each agency is set equal to zero. The distance between each grade is equal to one divided by the total number of grades that the agency applies. *CRISIL* has the lowest number of grades, an 8-point scale ranging from mfR8 to mfR1, whereas *Planet* has the highest number of grades, an 11-point scale ranging from e to a+.[2] The applied procedure is similar to the ones used in classical studies on determinants of credit ratings. For instance, Horrigan (1966) converts the rating scale to a 9-point scale, where each letter grade is assigned a value from 1 to 9 (Kaplan & Urwitz, 1979).

The rating grade is measured on an ordinal scale. Thus, ordered logistic regression is applied when (1) is run (Greene, 2003). For each rating agency, larger values correspond to better grades. As the players of the industry are not expected to have detailed knowledge about the various rating agencies, we start out with a pooled analysis in order to focus on the general determinants of rating grades in the microfinance industry. However, even if such combination of ordinal scales is an issue that has attracted much attention in social sciences (see, for instance discussion in Natarajan,

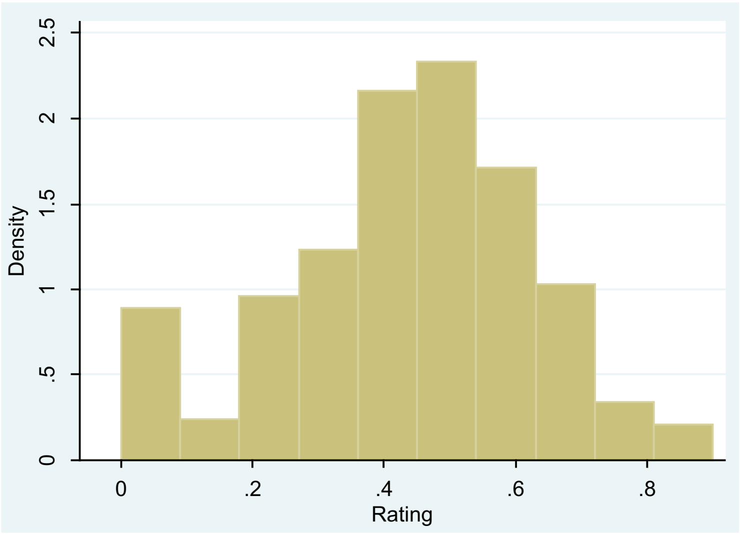

Figure 1. Rating distribution

Note: Figure 1 displays the distribution of the rating grades across the five rating agencies. 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.

McHenry, Lipsitz, Klar, & Lipshulz, 2007), the reader should be aware that it is not straightforward to combine different ordinal scales into one numerical scale. Noting this caveat to the analysis, we believe that the aggregation of scales can be justified by the fact that we complement the pooled analysis with agency-specific studies. Moreover, we also believe that our approach can be defended due to the relatively equal number of grades across agencies as well as our experience that the players in the microfinance industry appear to perceive a median rating grade as an indication of average performance, irrespective of rating agency. The drawbacks with the agency-specific analysis are that by estimating each equation separately, one does not make full use of all available information (see discussion in Kaplan & Urwitz, 1979), and, due to a limited number of observations, one is neither able to analyze an extensive set of alternative proxy variables for the various rating determinants nor able to include a sufficient number of control variables in the analysis.

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. However, a rather large proportion of MFIs (26 observations) were assigned a poor grade, making the distribution somewhat skewed to the left.

Table 2. Descriptive Statistics

Variable	Mean	Q1	Median	Q3	*SD*
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

Note: Table 2 displays descriptive statistics for the MFI (microfinance institution) ratings and the 6 main explanatory variables: MFI size, profitability, efficiency, risk, social performance, and solvency. The five analyzed rating agencies 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, PAR30; social performance is the average loan size adjusted for the GDP (gross domestic product) of the country where the MFI is located, AVG_LOAN_PPP; and solvency is debt divided by equity, DEBT/EQUITY. The 304 observations cover five rating agencies: Microrate, Planet, Microfinanza, CRISIL, and M-CRIL. The ratings cover the period 2001 to 2008.

We use the log of total assets as our primary size variable. Profitability is measured through return on assets, and operating expenses relative to total loan portfolio form the efficiency measure. Risk is measured as the share of the loan portfolio with more than 30 days in arrears (PaR30). The social performance indicator is the average outstanding loan amount adjusted for GDP in the countries where the MFIs are situated (Mersland & Strøm, 2010). These listed explanatory variables are the same as those used in Gutiérrez-Nieto and Serrano-Cinca (2007). We add the debt-to-equity ratio as our measure of solvency. Later, 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 average rating grade is 0.4321[3]. The mean of the log of total assets is 15.1416, which corresponds to US$3.8 million. The profitability measured by the return on assets is 3.2% on average. The MFIs have operating expenses relative to their loan portfolio equal to 27.7%, illustrating the high cost associated with small loans. The mean for portfolio at risk is 5.83%, and the average GDP-adjusted loan size is US$1.137. The mean debt-to-equity ratio is relatively high at 6.82, but its median value is only 1.66, illustrating the wide variety in MFIs' funding structures.

Empirical Analysis

The subsection Determinants of MFI Ratings in a Pooled Sample analyzes the determinants of MFI ratings in a pooled sample and the subsection titled Agency-Specific Determinants of MFI Ratings repeats the analysis on agency-specific samples.

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*

Note: 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. Numbers in italics denote significance at 5% level with two-sided tests.

Determinants of MFI Ratings in a Pooled Sample

Similar to Gutiérrez-Nieto and Serrano-Cinca (2007) we begin our analysis of the factors explaining MFI ratings by evaluating the ratings' pairwise correlation coefficients using the explanatory variables. Table 3 presents the standard Pearson correlations (below the diagonal) and nonparametric Spearman correlations (above the diagonal). Because of the ordinal scale of the rating grade, it is advisable to consider the Spearman correlations when analyzing correlations between the rating grade and the explanatory variables. However, as it turns out, the two correlation matrices present very similar results. Consistent with Gutiérrez-Nieto and Serrano-Cinca's findings and our hypotheses, the correlation analysis shows that size and profitability are positively related to ratings whereas operating expenses and risk are negatively associated with ratings. Solvency and social performance seem not to influence ratings. However, to draw conclusions on the basis of simple correlations is premature; thus, we use a multivariate setting to analyze these statistical associations as outlined in the section Theoretical Background, Hypotheses, and Research Design. Table 4 reports the findings.

In the first column of Table 4 the control variables are left out to allow comparison with forthcoming agency-specific analyses (Table 5) where too few observations cause "overfitting" and severe multicollinearity if controls are included. However, Table 4 suggests that the explanatory variables' significance level is hardly affected at all by the inclusion of controls. Also note that the mean variance inflation factor (VIF) is considerably below the often-emphasized threshold of 10 in all regressions, suggesting that serious multicollinearity is not an issue in any of the analyses.

Table 4 shows that MFI size is significantly positively related to MFI ratings, as suggested by the correlation analysis.[3] The preliminary findings from Table 3 are also confirmed for profitability, cost efficiency, and risk. This result means that the larger,

Table 4. Regression Analysis

	Without Controls		With Controls	
Variable	Coefficient	z Value	Coefficient	z Value
LN(ASSETS)	0.8388***	8.41	1.3131***	9.79
ROA	6.0256***	3.65	8.3134***	4.38
OEX_PORTF	−1.9325***	−3.18	−2.2608***	−3.22
PAR30	−12.0337***	−6.58	−11.4413***	−5.65
AVG_LOAN_PPP	0.0000	−0.64	0.0000	−0.93
DEBT/EQUITY	−0.0012	−1.04	−0.0023*	−1.92
Controls				
GDP_GR	—	—	−0.8351	−1.60
HDI	—	—	3.2792***	3.24
AGE_MFI	—	—	−0.0469***	−2.68
Indicator variables				
Year	—	—	Yes	—
Region	—	—	Yes	—
Type	—	—	Yes	—
Agency	—	—	Yes	—
Mean VIF (variance inflation factor)	1.07		6.73	—
Pseudo R^2 (%)	10.62		18.75	—
Number of observations	304		302	—

Note: Table 4 displays the results of multivariate analyses of the influence of MFI (microfinance institution) size, profitability, efficiency, risk, social performance, and solvency on MFI ratings. The results of the following ordered logistic regression are presented, with and without control variables, respectively:

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

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 (2001-2008), *Region* is a set of indicator variables for the MFIs' geographical locations (Latin America, Africa, Middle East and North Africa, Eastern Europe and Central Asia, and Asia), *Type* is a set of indicator variables for MFI type (bank, nonbank 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, z values, mean variance inflation factor (VIF), explanatory power (Pseudo R^2), and number of observations. One (*), two (**), and three (***) asterisks denote the conventional 10%, 5%, and 1% significance levels, respectively.

Table 5. Agency-Specific Analyses

	MICRORATE		PLANET		MICROFINANZA		M-CRIL	
Variable	Coefficient	z Value	Coefficient	z Value	Coefficient	z Value	Coefficient	z Value
LN(ASSETS)	1.35560***	4.03	1.4031***	7.05	1.5640***	5.80	1.2440***	3.64
ROA	11.5663**	2.25	13.2931***	4.81	11.5821***	2.85	5.2941**	2.55
OEX_PORTF	−2.4493	−1.54	−0.9468	−1.05	2.7169*	1.67	3.9025	1.35
PAR30	−16.6377***	−3.61	−8.8079***	−2.93	−16.5750***	−3.90	−19.4554***	−2.78
AVG_LOAN_PPP	0.0000	−0.10	−0.0002	−1.52	0.0000	0.02	−0.0001	−1.00
DEBT/EQUITY	−0.0687*	−1.77	−0.0092	−0.99	−0.0341	−1.42	−0.0013	−1.10
Mean VIF	1.61		1.14		1.14		1.18	
Pseudo R^2 (%)	26.61		24.73		23.25		19.08	
Number of observations	55		122		80		40	

Note: Table 5 displays the results of multivariate analyses of the influence of MFI (microfinance institutions) 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 ordered logistic regression are presented per agency:

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

The variables are defined in Table 4. The table reports regression coefficients, z values, the mean variance inflation factor (VIF), explanatory power (Pseudo R^2), and number of observations. One (*), two (**), and three (***) asterisks denote the conventional 10%, 5%, and 1% significance levels, respectively.

more profitable, more efficient, and less risky MFIs receive better ratings. However, neither the GDP-adjusted average loan nor the debt-to-equity ratio is a significant explanatory variable. Thus, rating grades appear unaffected by the MFI's social returns or its solvency. The analysis inclusive of control variables shows that MFIs situated in more developed countries (better HDI) receive better ratings than others. In addition, 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. Our interpretation of this is that the rating agency also considers itself as a motivator of MFIs, but this result should encourage researchers to explore lifecycle issues for MFIs. How do MFIs evolve over time?

Even if ordered logistic regression is our preferred statistical method for the agency-specific analysis, one may argue that canonical correlations (see Rencher, 2002) should be used for the pooled sample.[4] This argument arises from the agencies' use of different rating scales. As a robustness check (unreported), canonical correlations have been estimated. In the reduced model without control variables, there are no differences compared with the results reported using ordered logistic regression. In the full model, solvency, as measured by the debt-to-equity ratios, appears to be significant. Moreover, efficiency is no longer significant. All regressions have also been run using ordinary least squares. In addition, here, except for solvency being significant in the full model, there are no differences with the reported results.

All regression results are tested for the effect of possible outliers and influential points (not tabulated). First, we rerun the regressions using a trimmed sample. The 1st and 99th percentiles for the dependent variable and the 6 explanatory variables are deleted. The results are very similar to those of the main analysis. However, the significance level of efficiency is decreased in the analysis inclusive of control variables, and this variable is now not significantly related to rating grades. Second, we winsorise the explanatory variables such that the 1% lowest and highest values are replaced by the 1st and 99th percentile, respectively. This replacement does not affect the findings in the regression without control variables, but solvency, as measured with the debt-to-equity ratios, is significant in the regression with control variables. Third, we run the regressions on the full sample, compute residuals from the regression analysis, and rerun the regressions exclusive of variables with a residual larger than 2 standard deviations. This procedure does not affect any of the findings reported in Table 4. Overall, the results on size, profitability, risk, and social performance appear to be robust.

When assigning a rating grade to an MFI, the rater may not only consider current performance but also analyze historical performance (a factor not considered in Gutiérrez-Nieto & Serrano-Cinca, 2007). Thus, we rerun the regressions using lagged values of the explanatory variables (not tabulated). In this test, efficiency is no longer a significant explanatory variable. If the average of the current and lagged values of the explanatory variables is used in the regression, the results are equivalent to the ones reported in Table 4. These alternative tests suggest that historical observations are also relevant in explaining MFI ratings, but the conclusions on determinants of the ratings remain unaffected.[5]

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 (not tabulated). First, instead of the log of assets the log of total loan portfolio or the log of total number of clients could have been proxies for size. However, the results are insensitive to the proxy chosen. The reported results are also insensitive to the profitability proxy chosen. The adjusted return on assets,6 the operational self-sufficiency (OSS), and the financial self-sufficiency (FSS)[7] are all significantly positively related to the ratings.

The results on efficiency are sensitive to the proxy variable chosen. If the operating expenses are divided by total assets or total number of clients, instead of total loan portfolio, efficiency is no longer significant. This result also occurs if personnel productivity, defined as the total number of loan clients divided by the total number of employees, is used as an efficiency indicator. Thus, these additional regressions with alternative measures for efficiency, together with the finding in the canonical and trimmed sample regressions reported above, indicate that whether efficiency actually influences ratings remains uncertain. As for risk, portfolio write-offs and the risk coverage ratio8 are tested as alternative explanatory variables. Total write-offs are a significant explanatory variable, whereas the risk coverage ratio is not. An alternative test, with the sum of PAR30 and portfolio write-offs as the risk proxy, is significantly negatively related to the ratings. Collectively, the results on risk are robust and suggest that higher risk is associated with poorer ratings.

Social performance is the variable of this study that probably is the most complex to measure (Mersland & Strøm, 2010). Furthermore, even if the GDP-adjusted loan size is the most frequent proxy for social performance used by researchers as well as donors and investors (Cull, Demigüc-Kunt, & Morduch, 2007, Mersland & Strøm, 2010), one may claim that this variable does not fully capture the social performance dimension. Thus, we also test alternative proxy variables (see Gutiérrez-Nieto & Serrano-Cinca, 2007). First, we apply average loan size without the GDP adjustment. Second, we reintroduce the personnel productivity variable, but this time as a measure of social performance.9 Finally, we test the percentage of female clients as a social performance indicator. None of these alternative proxy variables is a significant explanatory variable for the MFI rating, and our conclusion on social performance appears to be robust. Thus, one may question the claim that the performance assessment ratings measure a combination of creditworthiness, trustworthiness, and excellence in microfinance (see http://www.ratinginitiative.org).

Several alternatives also exist when it comes to choosing a solvency proxy. The debt-to-equity ratio is typically listed as the main solvency variable in the finance and accounting literature (see, for example, Penman, 2010) and is probably frequently applied by potential investors as a long-term risk proxy. Likewise, bank regulators impose maximum levels of debt to equity, typically near a 10:1 ratio. Moreover, the debt-to-equity ratio is specifically mentioned by rating agencies (e.g., *Planet*) as a performance indicator applied when assigning the rating grades. Nevertheless, this measure is not significant as an explanatory variable in our main analysis. The capital structure could have also been expressed as the debt-to-assets ratio, the long-term debt-to-assets ratio, the loan portfolio-to-assets ratio or even the fixed assets-to-total assets ratio, but none of these variables is significant if applied as solvency measures in the regression analysis. Current assets divided by short-term debt is also tested. This ratio is a more short-term solvency indicator than the debt-to-equity ratio and may also be regarded as a proxy for liquidity. The variable is, however, not significant. Overall, it appears that there is no statistical influence from solvency on ratings.[10] The missing relationship between solvency and the rating might explain why the Afghanistan MFI Normico received a good grade shortly before it went bankrupt, compared with the anecdote in the section Introduction. As far as we know, no research on the possible correlation between the ratings and later financial problems exists. This issue should be given priority in future research.

Except for solvency, the findings indicating that the main 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), purely 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.1[1]

Agency-Specific Determinants of MFI Ratings

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). The regression analysis is repeated using the following subsamples: *MicroRate*, *Microfinanza*, *Planet Rating*, and *M-CRIL*. We do not report separate results for *CRISIL* because the number of observations available for this agency is too low.

Table 5 shows that size and profitability are significantly positively related, and risk is significantly negatively related to MFI ratings for all agencies. Consistent with the pooled sample analysis, neither solvency nor social performance appears to be statistically associated with the ratings. A particularly interesting result emerges when efficiency is analyzed. In the main analysis in Table 4, efficiency was significantly positively related to ratings; the higher the efficiency, the better the rating. However, in this agency-specific analysis, efficiency is no longer significant. In fact, efficiency, as measured by operating expenses divided by total loan portfolio, is not significant in any of the four subsamples. The section Determinants of MFI Ratings in a Pooled Sample stated that the results on efficiency were sensitive to outliers, the statistical method, and the efficiency proxy analyzed. Although the lack of significance in the agency-specific analysis can be driven by a small sample, the analysis confirms previous results that the influence of efficiency can be questioned. One should expect that ratings that are supposed to measure how well MFIs are functioning (i.e., the degree to which they fulfill their objectives) reflect MFI operational efficiency. Lack of efficiency is often considered a major challenge for MFIs (see, for example, Fitch Ratings, 2008; Sinha, 2002). If the relationship between the assigned ratings and MFI efficiency is not clear-cut, one risks that MFIs do not improve efficiency levels because a high degree of efficiency is not required for them to receive a good rating.[12]

Even though all rating agencies include information about social performance in their reports, few of the rating agencies state explicitly that social performance is evaluated when the rating grade is assigned. One exception is *Microrate*, which assigns the maximum score to an MFI "consistently exhibiting a clear, rational, and balanced relationship among the social, financial, and operational considerations of sound microfinance practice" (Gutiérrez-Nieto & Serrano-Cinca, 2007, p. 446). However, even for Microrate, it is impossible for us to document a statistical relationship between the ratings and social performance. However, we cannot fully rule out that the lacking significance can be attributed to the previously discussed challenges related to summarizing social performance in proxy variables.

Note that the explanatory power, as measured with the pseudo R^2, is considerably higher in the agency-specific analysis than in the pooled sample.[13] This difference can be attributed to regression coefficients varying across the samples. Thus, the importance of the various determinants varies across the agencies. For instance, for a standardized variable such as return on assets, the importance of the determinant seems to be considerably higher in the *Planet* sample than in the *M-CRIL* sample. However, with respect to which variables are significant drivers of the ratings, the results from the four samples are remarkably consistent. If weakly significant variables are disregarded , the exact same explanatory variables appear to be significant and nonsignificant, respectively, in the four samples. Thus, even if the agencies all have their own methodology and claim to assess different performance indicators, in practical terms, the drivers of the ratings appear to be very similar.

On the basis of the assumption that ratings may be dependent on older information rather than just on the current values of the explanatory variables, all regressions in Table 5 are rerun using explanatory variables that are lagged 1 year (not tabulated). The significance level of profitability is reduced for some of the agencies, but collectively, none of the conclusions is affected. 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), it should be noted that the explanatory power generally is lower when lagged variables are applied. Thus, the most recent observations on the determinants appear to be the ones most closely related to the ratings.

Summary and Concluding Remarks

In light of the recent critique of microfinance, there is an increased need for independent information about the operation of the MFI. In this regard, rating reports are interesting. This study presents a comprehensive multivariate analysis of the relationship between MFI ratings, 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 indicate that MFI size and profitability are positively related to MFI ratings and risk is negatively related to ratings, as expected. Efficiency is positively associated with the ratings in the pooled sample, but there is no statistically significant relationship in the agency-specific analysis. Moreover, the results on efficiency are sensitive to the inclusion of outliers and the statistical method chosen as well as to the proxy variables applied in the analyses. Regarding social performance and solvency, we are unable to document any statistically significant relationship with the rating grade.

In this study, we investigate the general determinants of MFI ratings across different agencies. The results from the agency-specific analysis suggest remarkably consistent information content across agencies. Such similarity improves the usefulness of the ratings, as donors and investors need not worry which specific agency has issued the assessment. Obviously, an alternative method for interpreting the ratings is to study each agency's official rating methodology. However, this study suggests that stakeholders should exercise some care in applying such an approach. For instance, we do not find a statistical association between the ratings and the debt-to-equity ratio in the *Planet* sample, even if *Planet* lists this ratio as a key performance indicator. Furthermore, we are unable to statistically document the claimed relationship between *Microrate's* rating grades and social performance. An interesting extension of this study would be to compare the drivers that the agencies claim to use with the drivers that the statistics indicate that they actually use.

A typical MFI has multiple bottom-line objectives and is expected to deliver both financial and social results. MFI ratings are supposed to measure a combination of creditworthiness, trustworthiness, and excellence in microfinance (http://www.ratinginitiative.org). However, the fact that rating agencies now offer specialized social ratings is an indication that the agencies have found it difficult to include social performance when setting the rating grade. Moreover, the finding in this study and in the former Gutiérrez-Nieto and Serrano-Cinca (2007) study clearly indicate that social performance is not part of the equation when setting the rating grade. Rating agencies, and those promoting the rating industry, should therefore make sure that stakeholders and users of rating reports know that the rating grade is set based on financial performance and not social performance. In view of this, the recent initiatives to launch separate social ratings seem logical and a step forward in the MFI rating assessments. In light of recent critiques of microfinance, such social ratings should particularly address whether MFIs practice heavy-handed collection methods and charge usury interest rates.

Overall, microfinance ratings appear to be comparable to traditional credit ratings. The determinants documented in this study are, to a large extent, similar to the determinants found in classical studies of credit ratings. It thus seems timely for donors to ask whether subsidizing specialized microfinance rating agencies makes sense. In the long term, it may be better for MFIs to be mainstreamed into traditional rating agencies, at least if the specialized ratings do not provide additional value. Moreover, because this study suggests that specialized agencies do not consider solvency risk, traditional credit raters are probably better able to provide true risk ratings for MFIs. Alternatively, if specialized ratings can demonstrate better specific microfinance knowledge, and if social performance can be fully separated in special ratings, a shift toward more pure financial ratings including efficiency standards seems logical. In general, specialized ratings may have fostered a higher degree of transparency in the microfinance industry, but the quality of the ratings remains debatable and deserves more attention by industry stakeholders and researchers. In future research it will be particularly important to determine whether MFI managers use rating information to improve operations and to what extent funders make use of rating information.

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Notes

1. Rating agencies argue that their ratings are broader than traditional credit ratings. However, whether social performance can be expected to influence the ratings is unclear since several MFI (microfinance institution) raters have recently started to offer specialized social ratings. However, the social ratings available are still few and thus, in this article, we focus fully on performance assessment ratings, also sometimes called global risk assessments. Moreover, to be able to compare our results with Gutiérrez-Nieto and Serrano-Cinca (2007), we include social performance in our analyses.
2. The + and – used in *Microfinanza's* ratings are used to indicate slight differences in the rating grades. In the standardization of the rating grades in the database, we have ignored this minor differentiation.
3. We apply the term *significant* when the significance level as measured by the *p* value is below .05 using a two-sided test.
4. Canonical correlations are sometimes criticized for being too flexible; other statistical techniques, such as ordered logistic regressions, impose more rigid restrictions, and it is generally assumed that the information obtained from other techniques is statistically more robust and can be presented in a more interpretable manner (Hair, Black, Babin, & Anderson, 2010).
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 autocorrelated.
6. Because subsidies are common in microfinance, *AROA* can be used as a subsidy-adjusted indicator; it is calculated by rating agencies and is often used as an alternative to the standard *ROA* measure.
7. Operational self-sufficiency (OSS) indicates whether operating income covers operating costs. Financial self-sufficiency (FSS) adjusts OSS for subsidies and other MFI-specific accounting issues.
8. The risk coverage ratio measures the share of the loans that are 30 days past due and are covered by default provisions in the MFI's financial statements.
9. More customers per staff member can be considered an indicator of efficiency, but with fewer customers per staff, there should be more room for advice and mentoring, and thus, the variable can also be seen as a proxy for social performance.

10. According to the Basel Capital Accord I & II, the Tier I capital ratio, defined as core equity capital to total risk-weighted assets, is the core measure of a bank's financial strength. However, no data set exists for MFIs that include risk-weighted assets, and generally, most MFIs have nearly all their assets in short-term microcredit loans.
11. Aquino (2010) provides a comprehensive literature review of the use of financial indicators in credit ratings.
12. Efficiency remains nonsignificant if canonical correlations are applied instead of ordered logistic regression. The only difference in the four samples to the results reported in Table 5 is that solvency appears significant in the *Microrate* sample when canonical correlations are used.
13. If standard OLS (ordinary least square) is applied, the explanatory power can be compared with the early studies on the determinants of credit ratings. In his classical study, Horrigan (1966) reported an explanatory power of just more than 50%. The explanatory power of the agency-specific regressions varies from 46.76% to 70.87% if OLS is applied. The weighted average of the adjusted R^2 is 62.02%. Thus, our models appear to be well specified, capturing much of the information relevant in computing MFI ratings.

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Bios

Leif Atle Beisland is an associate professor at the University of Agder in Norway. He holds a PhD in capital market based accounting research from the Norwegian School of Economics. His research covers both general accounting research and more specific research on financial reporting in the microfinance industry. He is also involved in several research projects on the use of microfinance services among persons with disabilities.

Roy Mersland is an associate professor in International Business at the University of Agder. He has extensive international management, consulting and research experience in the field of microfinance. He is the director of the Norwegian Centre for Microfinance Research and he is member of the Centre for European Research in Microfinance in Brussels (CERMi).