Information, the Cost of Credit and Operational Efficiency: An Empirical Study of Microfinance

Mark J. Garmaise
UCLA Anderson

Gabriel Natividad
NYU Stern

Abstract

We provide direct evidence on the impact of asymmetric information on both financing and operating activities through a study of credit evaluations of microfinance institutions (MFIs). We employ a regression discontinuity model that exploits the eligibility criteria of an evaluation subsidy offered by a non-profit consortium. Evaluations dramatically cut the cost of financing. This effect is strongest for commercial lenders and for short-term MFI-lender relationships. The impact of evaluations on the supply of finance is mixed. Evaluated MFIs lend more efficiently, extending more loans per employee.

We thank Damian von Stauffenberg and MicroRate for providing the data. Natividad thanks CIBER at UCLA Anderson for financial support. We have benefited from the comments of Bruce Carlin, Matthias Kahl, Philipp Schnabl, and seminar participants at UCLA Anderson.

Introduction

Asymmetric information plays a prominent role in modern theories of corporate finance, but empirically analyzing and assessing the impact of informational frictions has proven to be difficult. Credible exogenous information proxies are hard to find, and there are relatively few natural experiments that result in significant shifts in the information environment. As a result, in contrast to the significant and well-established stream of theoretical work on asymmetric information and financial contracting, empirical research in this area is still in a somewhat early stage of development (recent papers include Chiappori and Salanié (2000), Garmaise and Moskowitz (2004), Acharya and Johnson (2007), Karlan and Zinman (2008), and Hertzberg, Liberti, and Paravisini (2008)). This paper provides an empirical analysis of the effects of asymmetric information on both financing and operational activities through a study of microfinance institutions (MFIs), lending organizations based in emerging economies that provide small loans to relatively poor clients.[1] Our central strategy is to analyze a plausibly exogenous shock to the MFIs' information environment by exploiting the impact of a program offered by the non-profit Rating Fund to subsidize MFI credit evaluations. Restrictions in the eligibility criteria for the Rating Fund subsidy allow us to implement a regression discontinuity model that assesses the causal impact of credit evaluations. Viewing these evaluations as a means for reducing information problems, we consider the effects of credit evaluations by rating agencies on the cost of funds for MFIs. The Rating Fund program also allows us to investigate the relationship between the quality of publicly-accessible information about MFIs and their operating efficiency.

The microfinance setting is particularly appropriate for the study of the effects of information asymmetries on financing and investment for three reasons. First, information frictions are likely to play an especially important role in raising the

[1]Estimates place the size of the global microfinance industry at $15 billion (Consultative Group to Assist the Poor (2004b)) and the number of borrowers in the range of 50 million (Consultative Group to Assist the Poor (2004a)).

costs of finance in emerging industries and economies. In markets with less-well-established institutions and weaker regulations, adverse selection considerations will make it expensive for firms to raise funds and may restrict growth. We should therefore expect that information asymmetries would be especially salient in the young microfinance industry, which makes loans almost exclusively in less developed countries.

Second, MFIs play a financial intermediation role in their local economies that is quite similar to that played by banks. Understanding the impact of information asymmetries about financial intermediaries is important because frictions restricting the supply of financing to these intermediaries can quickly impede the flow of credit throughout the economy, as recent events have brought into relief. Last, the Rating Fund subsidy offers an unusual and specific shock to the level of information asymmetries that we can make use of to draw clear inferences in our empirical analysis.

The Rating Fund program provided a substantial co-payment to eligible MFIs that sought an evaluation after May 2001. The eligibility criteria involved strict cut-offs for minimal asset sizes and maximal average loan sizes. Our empirical approach is to measure the discontinuous financing and operational changes experienced by a given MFI precisely as it crosses the boundaries into (or out of) eligibility; we essentially contrast the MFI as it just meets the eligibility criteria with the same MFI (in a different year) as it falls just outside the criteria. We view the ratings subsidy program as essentially creating a supply of new information about eligible MFIs. It is clear that MFIs (and firms in general) choose whether to seek credit evaluations, so it may be difficult to draw causal inferences from observed correlations between credit ratings and the financial activities of an MFI. We show, however, that crossing into eligibility for the Rating Fund program led to a significant increase in the probability that an MFI was evaluated. This enables us to use crossing into eligibility as an instrument for evaluation, thereby avoiding issues surrounding the endogenous choice by an MFI of whether to be evaluated. In essence, the Rating Fund offered MFIs an opportunity to make a subsidized investment in transparency.

Our data provide loan-level information on the rates lenders charge MFIs. Using the instrumenting strategy, we find that evaluations dramatically reduce the cost of finance for MFIs. The interest rate paid by a given MFI to a fixed lender decreases by 550 basis points after an evaluation (the mean interest rate in the sample is 800 basis points). Our regression discontinuity instrumenting approach allows us to interpret this effect as causal — by reducing information asymmetries, credit evaluations make financing much less expensive for MFIs.

The benefits of evaluations vary across different segments of the MFI industry. MFIs receive funds from both non-commercial (e.g., governments or aid agencies) and commercial (e.g., banks or commercial funds) sources. We find that evaluations have a particularly strong effect in reducing the costs of financing from commercial lenders, which is consistent with the idea that these lenders are more sensitive to credit assessments of MFIs. We further show that evaluations do not have any significant impact on the rates charged by long-term lenders to a MFI, but they substantially reduce the rates charged by recent lenders. This suggests that the information asymmetries resolved by the credit evaluations are more useful to lenders who have only been dealing with the MFI for a short time.

While credit evaluations clearly reduce the price of financing for MFIs, the evidence for their impact on the quantity of finance supplied is mixed. We find that evaluations do not significantly increase the amount of loans that MFIs receive from outside creditors.

Our empirical approach allows us to assess the impact of asymmetric information on not only financing but on the operational activities of MFIs, as well. We are thus able to offer some direct evidence on the real effects of asymmetric information. Evaluated MFIs increase the number of clients per credit officer. Our results indicate that relieving information problems can significantly enhance operational efficiency (Bernardo, Cai, and Luo (2004) and Marino and Matsusaka (2005)).

To gauge the robustness of our results, we consider an alternate specification in which we instrument for the presence of an evaluation after the initiation of the Rating Fund using an indicator for whether an MFI met the program eligibility criteria *prior* to the announcement of the fund. It is clearly implausible that MFIs manipulated their characteristics to be be eligible for the subsidy before there was any knowledge of the Rating Fund. Using this instrument we find confirming evidence that the Rating Fund increased the probability of an evaluation for subsidized MFIs and that evaluations led to reduced financing costs and more clients per credit officer.

Our findings relate to the recent literature showing the relevance of ratings for firms' financing (Cantor (2004), Kisgen (2006), Odders-White and Ready (2006) and Sufi (2009)). In contrast to Sufi's (2009) finding in his sample of large U.S. firms that ratings increased the supply of finance and had no significant impact on price, we show that for the MFIs we study credit evaluations significantly reduced the price of financing while having a mixed impact on quantity. These varying results may be driven by differences between the information environment faced by a large U.S. company versus that faced by a relatively small MFI in a developing country. Our findings imply that the impact of asymmetric information may be non-uniform across heterogeneous settings. Our work also indicates that evaluations serve to change the way MFIs operate, which suggests an on-going role for evaluators in improving performance.

We present clear evidence that rating agencies promote microfinance, and in this way we contribute to the large and growing general microfinance literature (e.g., Brau and Woller (2004), Armendariz de Aghion and Morduch (2005), Karlan (2005), Khandker (2005), Bubna and Chowdhry (2007) and Karlan and Zinman (2009)). One central issue in the microfinance literature is the tension between those focused on securing the financial viability of MFIs and those who argue that emphasizing purely financial goals will lead MFIs to depart from their basic social mission of reducing poverty (Morduch (2000)). To address the issue of social impact, we analyze the effect of evaluations on the average size of loans originated by MFIs. (This is a common metric for social outreach, under the assumption that smaller loans are made to poorer clients.) We find no evidence that evaluations lead MFIs to concentrate their lending in large loans to presumably wealthier borrowers- average loan size is unchanged after an evaluation. Transparency in emerging markets may thus bring benefits to broad sectors of the population. Our findings suggest that credit agency evaluations are likely to promote the financial goals of MFIs without detracting from their social missions.

Our findings linking asymmetric information, third-party evaluations, the price of credit and the operations of the firm have broad application in many areas of finance beyond MFIs. This paper also provides a general insight into the substitutability of lending relationships and credit ratings. Existing lenders acquire information through relationships. Potential lenders acquire information through external institutions such as credit rating agencies. This paper argues that new credit ratings can benefit new lenders and lower the cost of financing supplied by these lenders. When the provision of the new credit ratings is unexpected (as in our setting), the resulting competition between new and existing lenders may benefit borrowers. On the other hand, the long-run effects of credit ratings in potentially discouraging lending relationships may not be wholly beneficial to borrowers, though this issue is outside the scope of this paper.

The rest of the paper is organized as follows. Section 1 describes the empirical setting and the data we use in the study. Section 2 provides an overview of the Rating Fund. The empirical specification for our tests is given in Section 3, and Section 4 discusses our results. Section 5 concludes.

1 The Global Microfinance Industry

A. Background [2]

Microfinance is a collection of practices built around providing small loans and

[2] This section is based on conversations with industry experts, participation in an MFI evaluation meeting, and online reports issued by MicroRate, the MIX Market, and the CGAP. For an excellent survey see Armendariz de Aghion and Morduch (2005).

accepting small saving deposits. Although traditional money lending has existed for centuries, the banking-like industry in which a microfinance institution (MFI) serves as a financial intermediary between owners of capital and needy borrowers is a relatively recent phenomenon that is expanding at a fast pace in Africa, Asia, Eastern Europe, and Latin America. This industry is the focus of our study.

Microfinance institutions have both important similarities and differences from traditional banks. On the one hand, MFIs raise funds, evaluate clients, grant loans, and collect payments with interest, all of these being essential banking activities. On the other hand, the loan-making processes, the client bases, the sources of funds, and the organizational forms of MFIs are quite different from those of global banks and even local banks in developing countries. Below we describe some of the most salient distinguishing features of MFIs.

A.1. MFI Products

MFIs provide small loans to both fund microenterprises and to directly finance consumption. The supported microenterprises typically have one employee (the owner) and may engage in small-scale retail sales (e.g. food vending or clothes selling), light manufacturing (e.g. production of handcrafts), services (e.g. bicycle repair) or agriculture (e.g. poultry raising) (Ssendi and Anderson (2009)). Some small businesses with multiple employees also receive microfinance backing. The direct consumption loans are made to individuals to finance the purchase of durables, to pay for children's tuition or to fund home improvements (McIntosh, Villaran, and Wydick (2008)). Business and household loans are both central components of microfinance, with the relative weighting between the two varying across MFIs and regions (Johnston and Morduch (2007)). These microenterprise and microcredit loans are often made to very poor borrowers, and this market segment has typically been considered unattractive by traditional banks. Overall, however, repayment rates in microfinance have been quite high (Morduch (1999)); in our data, which we discuss in detail in Section 1.C below, we find that the median portfolio quality (the proportion of the loan portfolio that is less than 30 days overdue) is 0.95.

In addition to the small average loan size, a second distinctive characteristic of microfinance loans is that, unlike bank loans, they are mostly made with little or no collateral (Johnston and Morduch (2007)). One mechanism sometimes used as a substitute for collateral is group lending in which borrowers (perhaps all drawn from a rural village or urban neighborhood) assume responsibility for each others' loans. Recent evidence, however, suggests that group lending may be no more effective in reducing defaults than standard individual lending, even in the absence of physical collateral (Giné and Karlan (2008)). MFIs have also extended their activities from loan-making to the provision of insurance against catastrophes or poor weather (Giné, Townsend, and Vickery (2007)).

A.2. Sources of Capital

The financing of MFIs differs from that of banks in two main respects. First, MFIs do not rely much on demand deposits. In our data, the mean ratio of demand deposits to assets is only 0.08 and the median is zero. Second, the debt financing of MFIs is provided by non-commercial lenders in addition to the usual commercial sources. Non-commercial loans are supplied by development agencies, governments, co-operatives and other MFIs. Important non-commercial financing sources include the Inter-American Development Bank and the World Bank. Non-commercial loans typically have a "social" flavor — the loans are designed to help less developed countries and regions achieve growth and poverty reduction.

Commercial loans are supplied by commercial funds, global banks and local banks. Some prominent sources of commercial funding include BlueOrchard (a microfinance investment firm headquartered in Switzerland) and the Global Commercial Microfinance Consortium (a microfinance fund launched by Deutsche Bank in 2005). As we discuss below in Section 1.C, commercial funding has significantly increased in importance recently. There is a growing interest among commercial investors and global banks in investing in microfinance for reasons beyond charity, as documented by Matthäus-Maier and Von Pischke (2006). There is a sense that capital is scarce in the developing world, and that investments there should earn higher returns (de Mel, McKenzie, and Woodruff 2008); as a result, MFIs are increasingly seen as commercially sound investment prospects.

A.3. Organizational Forms, Regulation and Compensation

MFIs may be either for-profit or not-for-profit entities. Non-profit MFIs are essentially non-governmental organizations (NGOs) with philanthropic goals that specialize in the provision of finance to the very poor. For-profit MFIs are owned by shareholders and governed by boards of directors. While this distinction seems quite clear, it is nonetheless the case that for-profit MFIs often maintain a sense of their social mission and not-for-profit MFIs are aware of their need to achieve financial sustainability in order to continue to perform their functions (Dorado and Molz (2005)). Even for-profit MFIs have a broader sense of their social goals than most local banks.

MFI regulations differ significantly across countries.[3] Typically, MFIs that do not fund themselves with deposits are not subject to regulations or disclosure requirements, while deposit-taking MFIs may be treated like banks. In some cases (e.g. Bolivia), MFIs have been brought into the regulated banking sector with a specialized set of guidelines. In other jurisdictions (e.g. Colombia), even large MFIs function as unregulated NGOs (Loubière, Devaney, and Rhyne (2004)).

In the development stage of the MFI industry in the early 1990s incentive schemes for managers were quite rare, but they have become increasingly popular over the last decade. Individual credit officers now typically receive monetary rewards for meeting benchmarks along a number of dimensions, including average collection rates, value of outstanding loans and number of clients. Socially-oriented MFIs tend to place a greater emphasis on the number of clients relative to shareholder-owned MFIs. Some MFIs also make use of team or branch-based compensation methods and institution-wide profit sharing has become more common. Managerial incentive schemes have become

[3]See the database at http://www.microfinanceregulationcenter.org for a summary.

especially popular in the more commercialized microfinance markets in Eastern Europe and Latin America (McKim and Hughart (2005))

B. Existing research

The explosive growth of microfinance is reflected in research. For example, Brau and Woller (2004) classify over 350 microfinance papers into six themes: financial sustainability, products and services offered, management and development, client targeting, policy and regulation, and social impact. Despite its breadth, previous research on microfinance is limited when compared to research on financial intermediation mostly because of its descriptive focus. For example, recent large-sample studies have documented the existence of profits (Cull, Demirguç-Künt, and Morduch (2007)) and a positive link between MFI performance and good macroeconomic conditions (Ahlin and Lin (2006)). A new stream of work, however, is using microfinance as a setting for randomized experiments aiming to address pending issues in economic research (e.g., Kaboski and Townsend (2008) and Karlan and Zinman (2009)). While some of these papers study information asymmetries and credit conditions, their focus is typically on the small borrowers who form the the client base of MFIs rather than on the MFIs themselves and how they are financed.

The work presented here extends the existing research on microfinance in several new directions. First, to our knowledge this is the first paper to empirically study the funding of MFIs in relation to information asymmetries. The microfinance literature has paid little attention to the liability side of MFIs (Jansson (2003)), and while previous work has described how MFIs get external ratings (Gutierrez-Nieto and Serrano-Cinca (2007)) and whether those ratings relate to funding (Hartarska and Nadolnyak (2008)), we are the first to confront information asymmetries directly and to offer causal evidence on this issue. Second, we explore how information asymmetries influence the pricing of capital received by MFIs at the level of each loan and funding relationship. This micro level of observation is unusual not only in microfinance but also in the general financial intermediation literature, as well (e.g., Petersen and Rajan 2002). Third, this paper explores how information asymmetries affect the real operation of MFIs. Beyond insightful case studies on the management of microfinance (e.g., Armendariz de Aghion and Morduch (2005), chapter 10), limited large-sample evidence exists on how MFIs operate to achieve efficiency. Fourth, we contribute to the current debate on the commercialization of microfinance by investigating whether MFIs stray from their social missions once information asymmetries are mitigated.

C. Data

Our main data source is a database of audited financial statements and selected operating variables on MFIs provided to us by MicroRate. Occasionally featured in industry publications (e.g., Stauffenberg and Abrams 2007) and general interest reports (e.g., *The Economist*, 5 November 2005), the data have been collected and maintained systematically by MicroRate, the oldest microfinance rating agency in the world, but never opened to research before. The data cover 138 MFIs over the period 1997–2008, as of 19 February 2009. MicroRate carries out both qualitative evaluations and quantitative ratings, visiting MFI headquarters and branches to gather information. All covered MFIs were evaluated and, in the latest years, assigned a quantitative rating by MicroRate at least once during the sample period. The data are presented mostly in a semester (6 month) basis. In the periods after an evaluation, MicroRate continues collecting information from each MFI, validating it for consistency and standardizing variables across MFIs in the database.[4] There are 1,380 MFI-period observations in total. The MFIs are drawn from 31 countries in Africa and Latin America.

The composition of the database shows a growing number of MFIs over the years. For example, the number of MFIs in the sample is 58 in 1997 and 127 in 2007. This trend could reflect the growth of the sector through entry, as the founding year of MFIs ranges from 1981 to 2008. Although we can only observe exit from the database and

[4]As described by Ahlin and Lin (2006) and Cull et al. (2007), an alternative database on MFIs is publicly available at the Mix Market (themix.org). Besides differences in coverage and depth, MicroRate guarantees the attributes of consistency and standardization hard to find in self-reported data.

not exit from the market, the age of an MFI is an important indicator of survival and success, and we will use it in the analysis of lending relationships and pricing.

One key aspect of MicroRate's database is the uniform expression of all variables not only within each MFI over time but also across all MFIs in the sample. For example, all audited financial statements are expressed in dollars and follow specific expression guidelines provided by MicroRate to each MFI, corroborated later by MicroRate's analysts.

The database provides audited information on both the financing and lending activities of the MFIs.[5] Table 1 shows some summary statistics. The median portfolio of loans given by an MFI is $4.67 million, and the median amount of financing received by the MFIs in a given semester is $3.32 million. The median size of a loan originated by an MFI is $590, and the median number of clients served by an MFI in a given semester is 12,950. As shown in Figure 1, the amount of lending per MFI and the number of clients per MFI both increased substantially during our sample period. The roughly ten-fold growth in the average number of clients per MFI from 1997 to 2006 is indicative of the dynamism of the MFI sector.

Because we observe each loan received by the MFIs, we are able to subdivide total financing of MFIs into non-commercial loans (supplied by development agencies, governments, co-operatives and other MFIs) and commercial loans (supplied by commercial funds, global banks and local banks). The median amount of commercial financing over the full data set is $0.33 million. As shown in Figure 2, however, commercial financing has grown dramatically over time both in absolute value and as a fraction of total funding. In 2007, the median commercial financing was $2.7 million.

[5] MicroRate's data on MFI liabilities are especially interesting in the context of a vast microfinance literature that has paid little attention to the capital structure of microfinance institutions, as pointed out by Jansson (2003).

2 The Microfinance Rating and Assessment Fund

The Microfinance Rating and Assessment Fund was launched by the Inter-American Development Bank (IDB) and the Consultative Group to Assist the Poor (CGAP) in May 2001 to promote the rating of microfinance institutions (MFIs). (The European Union later joined the fund in 2005.)[6] The fund was designed to encourage greater transparency in performance reporting by MFIs, with the broader goal of increasing the supply of commercial funding to the MFI industry.

The Rating Fund subsidized credit risk ratings supplied by a set of rating agencies from an approved list. (Some other services, such as assessments of whether an MFI met the expectations of its donors, were also subsidized.) The subsidies were on a declining scale: the initial rating was subsidized 80%, the second rating was subsidized 60% and the third rating was subsidized 40%. The subsidies also had caps that varied slightly across regions. For example, the initial rating cap was $8,000 in Latin America and the Caribbean and $10,000 in Africa. The subsidies were significant relative to the cost of a rating. For example, MicroRate's evaluations cost no more than $15,000.

The subsidy was limited to three ratings per MFI. MFIs that had received subsidies prior to the opening of the Rating Fund could still apply for the full slate of three subsidies, on the same terms as MFIs that had not previously been rated. The Rating Fund was quite popular: before closing at the end of 2007, the fund had subsidized over 400 reports. Of the 338 evaluations performed by MicroRate, 123 were subsidized by the Rating Fund.

2.1 Eligibility Criteria

Only MFIs satisfying the following criteria could apply for subsidies:

1. The MFI must have total assets between $300,000 and $30 million. For Latin

[6] The description of the Rating Fund in this section is drawn from ratingfund.org.

American (excluding the Caribbean) MFIs, the lower bound on assets was \$500,000.

2. The MFI must have an average outstanding loan size of less than \$2,000. For Latin American and Caribbean MFIs, the maximum average loan size was \$3,000.

While a small number of exceptions for marginal cases may have been made to these criteria to include additional MFIs, officials at the Rating Fund confirmed to us that the guidelines for eligibility were generally followed.[7]

3 Empirical Specification

Our tests focus on the impact of evaluations on the activities of MFIs. We analyze whether the provision of information via an evaluation leads to different financing and operational policies by MFIs. Specifically, we estimate equations of the following form:

$$MFIcharacteristic_{i,t+1} = \alpha + \beta * (evaluated_{it}) + \gamma * controls_{it} + \delta_i + \lambda_t + \epsilon_{it}, \quad (1)$$

where $MFIcharacteristic_{it}$ is some attribute of MFI i in period t, $evaluated_{it}$ is an indicator for whether MFI i was evaluated in period t, $controls_{it}$ is a vector of controls, δ_i is an MFI fixed effect, λ_t is a year fixed effect and ϵ_{it} is an error term.

MFIs choose whether or not to seek an evaluation. The endogenous quality of evaluation provision therefore makes it inadvisable to estimate equation (1) via ordinary least squares (OLS). For example, suppose that we consider the relationship between the

[7] MFIs typically hold loans and other assets that are denominated in non-dollar currencies. The CGAP standard for evaluating MFI grant applicants is to apply free market exchange rates for purposes of currency conversion. Average annual exchange rates are applied to income statement entries and year-end exchange rates are applied to balance sheet items (Isern, Abrams, and Brown 2008). The scope for MFI manipulation of exchange rates to artificially meet the eligibility criteria is thus quite limited.

amount of financing an MFI receives and whether or not it has been recently evaluated. It may well be the case that MFIs that have experienced recent success both seek additional financing (to continue their growth) and choose to be evaluated (because they prefer to be evaluated during successful periods); it is also possible that firms engage in rating shopping (e.g., Skreta and Veldkamp 2009). We might therefore observe a simultaneous correlation between the provision of financing and an evaluation, but this correlation would not show that evaluations actually lead to more financing in a causal sense.

In order to address this endogeneity concern, we propose a regression discontinuity approach.

3.1 Regression Discontinuity Design

The Rating Fund subsidy is large relative to the cost of an evaluation, so eligibility for the subsidy should be expected to increase the probability that an MFI pursues an evaluation. Moreover, MFIs that have total assets and average loan sizes just within the eligibility criteria will be able to access the subsidy, while MFIs with either total assets or average loan sizes just outside the criteria will not be able to use the subsidy. If the probability of an evaluation is continuous in assets and average loan size (in the absence of the subsidy), then any jump in the use of evaluations precisely at the eligibility boundaries may be attributed to the causal impact of the subsidy. As in a standard regression discontinuity design, this allows for consistent estimation of the effect of evaluations (Hahn, Todd, and Klaauw (2001)).[8] Our setting differs only in that there are multiple relevant discontinuities. Specifically, following the criteria in Section 2.1, we define the following indicator variables:

[8] A recent application of the regression discontinuity approach in finance is found in Sufi and Roberts (2009).

$$I_L = \begin{cases} 1 & \text{if avg. loan size} \leq \$2,000 \text{ in the MFI-year (Latin American MFIs)} \\ 1 & \text{if avg. loan size} \leq \$3,000 \text{ in the MFI-year (non-Lat.Am. MFIs)} \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

$$I_A = \begin{cases} 1 & \text{if assets} \geq \$500,000 \text{ in the MFI-year (Latin American MFIs)} \\ 1 & \text{if assets} \geq \$300,000 \text{ in the MFI-year (non-Latin American MFIs)} \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

$$I_T = \begin{cases} 1 & \text{if observation follows May 2001} \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

The Rating Fund subsidy will have an effect only in MFI-years for which all these indicators are positive,[9] so we can use these three discontinuities (in average loan size, asset size and Rating Fund period) to instrument for the endogenous variable $evaluated_{it}$. For each MFI-year, we define L to be average loan size minus the boundary described in (2) and A to be the asset size minus the boundary given in (3). We estimate

$$MFIcharacteristic_{i,t+1} = \alpha + \beta * (evaluated_{it}) + \nu_1 I_A I_L + \nu_2 I_L I_T + \nu_3 I_A I_T \tag{5}$$

$$+ \sum_{j=1}^{4} \omega_j^L L^j + \sum_{j=1}^{4} \xi_j^L I_L L^j + \sum_{j=1}^{4} \omega_j^A A^j + \sum_{j=1}^{4} \xi_j^A I_A A^j$$

$$+\gamma * controls_{it} + \delta_i + \lambda_t + \epsilon_{it},$$

and

[9] There are few MFIs that cross the upper \$30 million asset bound in our data, so we make use only of the lower bound and exclude MFIs with more than \$30 million in assets.

$$evaluated_{i,t} = \alpha' + \beta' * I_A I_L I_T + \nu'_1 I_A I_L + \nu'_2 I_L I_T + \nu'_3 I_A I_T \tag{6}$$

$$+ \sum_{j=1}^{4} \omega_j^{L'} L^j + \sum_{j=1}^{4} \xi_j^{L'} I_L L^j + \sum_{j=1}^{4} \omega_j^{A'} A^j + \sum_{j=1}^{4} \xi_j^{A'} I_A A^j$$

$$+\gamma' * controls_{it} + \delta'_i + \lambda'_t + \epsilon'_{it}.$$

That is, we instrument for $evaluated_{it}$ using the triple-discontinuity indicator $I_A I_L I_T$. We estimate this model using 2SLS (two-stage least squares) with robust standard errors that allow for arbitrary correlations over time for each MFI. (That is, we cluster at the MFI level.) We essentially use the regression discontinuity approach to generate an instrument for the 2SLS estimation.

This approach generalizes to multiple discontinuities the models of Card, Dobkin, and Maestas (2004) and Matsudaira (2008). The specification allows the probability of evaluation to be continuous in assets and average loan size, with the shape of the probability function permitted to be different on either side of the various eligibility criteria. (No time polynomials are included because they are subsumed in the yearly fixed effects.)

Our 2SLS regression discontinuity model exploits only the impact on a given MFI of crossing the precise eligibility boundaries during the Rating Fund period. The inclusion of the polynomial controls ensures the estimation picks up only the discontinuous effect on the MFI of just meeting the eligibility criteria relative to just falling short of the criteria. Only MFIs that cross the eligibility boundaries contribute to identification — the other MFIs are used as controls. While there may be trends that had differential effects on various sectors of the MFI industry over the sample period, our empirical model analyzes the role of evaluations by focusing on the discontinuous impact of crossing the specific Rating Fund eligibility boundaries. It is implausible that any such impact was driven by anything other than the Rating Fund subsidy itself.

It is certainly the case that MFIs can influence their level of assets and average loan size, but this potential for manipulation (e.g., to meet the program criteria) does not invalidate the regression discontinuity design. As long as the manipulation is imperfect and noisy (which seems quite reasonable to assume in this setting, given that the data are audited and eligibility is influenced both by free market currency exchange rates and by the actions of the MFI's borrowers, which the MFI cannot completely control), the regression discontinuity model is identified (Lee (2008)).

4 Results

4.1 Testing the Instrument

We begin by analyzing whether an MFI was more likely to receive an evaluation after just crossing the eligibility boundaries. That is, we estimate equation (6) of the regression-discontinuity model. Data is available for 925 MFI-period observations. (In all tests we use the complete sample for which data is available.) In the first column of Table 2 we report results from regressing a dummy variable for whether the MFI was evaluated during the current period on the triple discontinuity instrument and the full set of controls. The controls include the asset and average loan size polynomials (to the fourth degree), the indicators for asset, loan size and time period eligibility and their interactions with the polynomials, leverage (total book liabilities over total book equity), the ratio of demand deposits to total assets, the ratio of credit officers to total staff, MFI dummies and year dummies. The estimation is via OLS, with robust t-statistics clustered at the MFI level reported in parentheses.

We find that the triple discontinuity enters equation (6) significantly with a t-statistic of 3.72. MFIs that fell just within the eligibility requirements have a probability of evaluation that is 0.311 higher than those that fell just outside the requirements. This is quite a large increase in probability relative to the mean evaluation probability of 0.25 and suggests that the Rating Fund was quite important in promoting the overall use of evaluations by MFIs.

In the second column of Table 2 we display the results from a regression model that is identical to the previous one except that the polynomial controls are extended to the fifth degree. The estimated coefficient of 0.311 and t-statistic of 3.75 are very similar to those in the fourth degree model, demonstrating the robustness of our first finding. These results provide evidence that the Rating Fund subsidy indeed increased the probability of an evaluation for MFIs that met the asset and loan size criteria.

4.2 Evaluations and Pricing: Loan-level Analysis

In this section we consider the impact of evaluations on the terms of the financing offered. We analyze loan-level data that describe the interest rates paid by MFIs to their various lenders. We make use of MFI-lender pair fixed effects to analyze the effect of a credit evaluation on the rate paid by an MFI to a specific lender. While this specification resembles previous work analyzing loan-level data (e.g., Petersen and Rajan 2002), our use of pair-level fixed effects goes beyond lender or borrower characteristics to isolate linear relationship-level unobserved heterogeneity. We express interest rates in dollar terms, using forward exchange rates from Datastream to convert rates from loans priced in other currencies.

We consider the impact of evaluations on loan pricing, taking into account features of the loan and the nature of the relationship between the MFI and the lender. Specifically, we regress the interest rate on an indicator for whether the MFI was evaluated in the previous period, the loan amount (in logs), an indicator for U.S. currency loans, an indicator for short-term (less than one year) loans, the age of the MFI, the length of the relationship (i.e., number of semesters in which the lender has lent to the MFI), MFI-lender pair fixed effects and year fixed effects. The estimation is via

OLS, with robust t-statistics clustered at the MFI-level reported in parentheses. In this preliminary regression we simply include the evaluation dummy itself, setting aside for the moment endogeneity issues.

The results presented in the first column of Table 3 indicate that an evaluation is associated with an insignificant effect on the interest rate paid. There is, of course, significant selection in the process of seeking an evaluation. Perhaps only MFIs with improving prospects seek evaluations or, on the contrary, perhaps evaluations are only sought by MFIs in trouble who require outside validation. The insignificant raw partial correlation between evaluations and subsequent interest rates is difficult to interpret and may be driven by the qualities of the MFIs seeking evaluations rather than by a direct causal impact of the evaluations themselves. To address this potential issue, we adopt the two-stage regression discontinuity strategy described in Section 3.1 and estimate (5) and (6) where the dependent variable of interest is the rate paid by the MFI for its financing.[10] The results from the first-stage regression (6), detailed in the second column of Table 3, indicate that subsidy eligibility is significantly associated with the use of evaluations. Our instrumented estimate of the impact of evaluations on interest rates is given in the third column of Table 3: we find that evaluations have a negative and significant effect on rates. The magnitude of the effect is quite large: an evaluation in the previous semester reduces the rate on the loan by 550 basis points, a large drop relative to the 800 basis point average rate across all loans. As the clients of microfinance institutions are sensitive to the terms of the loans they receive (Karlan and Zinman 2008), our results suggest a key role for information production in lowering the cost of credit.

The triple discontinuity feature of the Rating Fund eligibility conditions limits the

[10] Our two-stage estimation for Table 3 does not follow the usual specification of a 2SLS design because in this case we use controls from the past and the present to explain the dependent variable in the present (i.e., interest rate), and it would be incorrect to use variables from the present to instrument for the endogenous variable of the past. So the models will instrument for evaluation lagged using only lagged variables in the first stage, introducing the contemporaneous variables in the second stage along with the instrumented variable and the other lagged variables.

extent of our graphical analysis, as we cannot visualize four-dimensional graphs. Figure 3, however, offers a partial illustration of our empirical design for the case of asset size, making use of equation (3). Around the eligibility zone, there is a sharp decrease in the average interest rate paid by MFIs to their lenders for those observations that barely pass the eligibility threshold, as compared to those that barely fail to pass it. Relative to the average interest rate of 0.08 (as expressed in decimals), the figure shows the large economic impact of evaluations.

4.3 Evaluations, Financing Terms and Cross-Sectional Characteristics

The results in Table 3 establish that evaluations reduce the rates paid by MFIs for financing. In this section we analyze for which MFIs the impact of evaluations is greatest. We split the sample into loans provided by commercial lenders (i.e., global and local banks and commercial funds) and non-commercial lenders (all other sources). As displayed in the first and second columns of Table 4, evaluations significantly reduce rates for both classes of lenders, but the effect is much larger for commercial lenders. This suggests that the information effects of evaluations are more important for commercial lenders, who are likely to be more sensitive to the profitability of the loan than the non-commercial lenders. Given the increasing role of commercial lenders described in Figure 2, the effects of evaluations on commercial lending rates are likely to be particularly important in the future.

We also split the sample into those MFIs that were founded before 1997 (the sample start period) and those that were founded in 1997 and thereafter, and we regress the interest rate paid by the MFI to its lender on an indicator for whether the MFI was evaluated in the previous semester and the full set of controls (including MFI-lender pair fixed effects) and use the regression discontinuity instrumenting strategy as before. As we show in the third and fourth columns of Table 4, evaluations significantly reduce rates for older MFIs. While this result is consistent with previous findings on firm age as a key covariate for debt characteristics (e.g., Faulkender and Petersen 2006), we would have expected that young MFIs benefit more from an evaluation, conditional on their credit quality being good. Because these qualities may only be observable to insiders in "soft information" banking, we expand our tests to look more carefully at age from the standpoint of a loan *relationship*.

We now divide the sample into loans made in the context of long-term (five semester or longer) and short-term (four semester or shorter) relationships between MFIs and their lenders. One hypothesis is that evaluations are more important in reducing rates in short-term relationships, because information asymmetries are much stronger in these relationships. An alternative hypothesis is that lenders in long-term relationships may be able to capture information rents and charge higher rates (Sharpe (1990) and Rajan (1992)) and that an increase in information supply via an evaluation may serve to particularly reduce the rents enjoyed by these lenders. As we show in the fifth and sixth columns of Table 4, evaluations have a much stronger effect in reducing rates in short-term relationships. This is consistent with the idea that these lenders can make use of the information in the evaluations to reduce the financing lemons cost.

4.3.1 Financial Rating

Beginning at the end of 2002, MicroRate included in its evaluations a quantitative rating of an MFI, on a scale from zero to nine.[11] We now consider the impact of this rating on the interest rate charged by estimating equation (5) with interest rate as the dependent variable, replacing the evaluation dummy with the credit rating granted by MicroRate. In untabulated results we do not find a significant coefficient on the financial rating. We are unable to instrument for the precise rating granted by MicroRate, so it is difficult to offer a clear interpretation of this finding. It may be, for example, that it is the initial

[11]MicroRate created a scale going from α^{++} to γ^{-}, which is translated into nine to zero for the empirical analysis performed here. The criteria for ratings are proprietary to MicroRate, and have become part of a current discussion on how MFI risk should be assessed. We have ratings for MFIs in 2,427 loan transactions.

evaluation that the market views as especially informative and that refinements of the rating methodology are less influential (or are perhaps anticipated).[12]

The basic intuition from the theoretical information literature is that it is the presence of information asymmetries that generates frictions. Evaluations reduce these asymmetries and thereby minimize the credit market distortions, even if it is the case that the information in the reports is, on average, neither good nor bad. Simply by providing investors with verified data and expert assessments of MFIs (members of a young and unfamiliar sector of the financial market), credit evaluations are able to reduce the cost of funds for microfinance.

4.4 The Real and Financial Effects of Evaluations

4.4.1 Quantity of Financing and Demand Deposits

The results in Table 3 show that evaluations reduced the price of financing for MFIs. We now consider the impact of these evaluations on the financing of MFIs and test the hypothesis that evaluated MFIs will receive more financing. We expect that any changes in financing policies by MFIs will occur at some point subsequent to being evaluated, and thus all the results we present describe financing two semesters after an evaluation. (Results at leads of three and four semesters are very similar.) In the first column of Table 5 we display the results from regressing the ratio of future short-term debt to assets on the instrumented evaluation variable and the full set of controls described above. The estimation is via regression discontinuity 2SLS. We find an insignificant (t-stat=-0.02) coefficient on the instrumented evaluation dummy. As detailed in Table 5 column 2, we also find that evaluations (instrumented) have an insignificant (t-stat=-1.17) effect on the future long-term debt to asset ratio; there is no clear evidence that evaluations have a meaningful effect on the quantity of financing received by affected MFIs.

While external financing in the form of loans is the main source of financing for the

[12] Tang (2009) discusses the effects of market expectations on the impact of credit rating changes.

MFIs in the sample, they also make some use of demand deposits (the mean deposits to assets ratio is 8%). We regress the ratio of deposits to assets on the instrumented evaluation dummy and the usual controls. As displayed in the third column of Table 5, evaluated MFIs receive significantly more demand deposits (t-stat=3.18).

These findings indicate that the primary effect of evaluations is to decrease the price of external loan financing, while leaving the quantity of external loan financing substantially unchanged and increasing the amount of deposits. Overall, these results contrast with the finding of Petersen and Rajan (1994) that small business lending relationships mainly lead to greater provision of financing with only a small impact on credit pricing. The primary impact of evaluations on microfinance institutions is to reduce to cost of financing.

4.4.2 Number of Clients

In this section we consider the impact of evaluations on the operational efficiency of MFIs. In particular, controlling for the number of credit staff, do evaluated MFIs deal with more clients? A regular regime of evaluations may encourage MFIs to professionalize and to perform more efficiently as they will be subjected to on-going scrutiny by an outside party. That is, evaluations may serve to offer a form of market discipline. Even though it is not clear that the reduced cost of funds associated with evaluations will increase efficiency (indeed, the opposite may be the case), evaluations may have a direct impact on MFIs: evaluated MFIs may understand that details on their operations will now be shared with the market and may therefore take care to improve their performance.

As previously, we consider outcomes two semesters in the future, and results are similar for three and four-semester leads. We regress the log of the number of MFI clients on (instrumented) evaluation and the standard controls (which include the number of credit staff). The regression results presented in the fourth column of Table 5 show that evaluations significantly (t-stat=2.37) increase the number of future clients.

As a related test, we regress the number of MFI clients per credit officer on (instrumented) evaluation and the usual controls. We find, as described in column five of Table 5, that evaluations lead to significantly (t-stat=2.03) more MFI clients per credit officer. These results show quite clearly that evaluations lead MFIs to make more efficient use of their credit personnel.

Our results on how information asymmetries affect the market expansion of financial intermediaries have broad implications, with particular importance in microfinance. While recent work (de Mel, McKenzie, and Woodruff 2008) suggests that the high returns of microenterprises in developing countries are due to the lack of capital in credit markets, our unique contribution is to document a specific channel for the expansion of microfinance operations.

4.5 Robustness: Eligibility Prior to the Rating Fund

The analysis in the previous sections is subject to the criticism that MFIs may exert control over their total assets and average loan size and this control may undermine the exogeneity of an MFI's eligibility for the Rating Fund. As we discuss in Section 3.1, as long as this control is not perfect and admits some noise, Lee (2008) shows that the regression discontinuity design is not invalidated. Nonetheless, in this section we consider an alternate specification to which this concern does not apply.

We propose an alternate 2SLS model in which we consider whether, in December 2000 (before the advent of the Rating Fund), an MFI met the subsequently announced eligibility criteria for the Rating Fund subsidy. (For three MFIs without data in December 2000, we use the June 2000 values.) Specifically, we re-estimate the base model, replacing the loan size and asset eligibility indicators (as described in equations 2 and 3) with indicators for whether the MFI met the Rating Fund criteria in December 2000. We then estimate (5) and (6) via a panel 2SLS regression, replacing the asset and loan size variables with their values in December 2000 and clustering at the MFI level.[13]

Our identification strategy is therefore to analyze the impact of the Rating Fund subsidy by contrasting the behavior before and after the initiation of the Rating Fund of the MFIs that met the asset and loan size criteria in December 2000. MFIs that did not meet the asset and loan size criteria in December 2000 simply help to better estimate the coefficients for the full set of controls. The Rating Fund subsidy is plausibly exogenous: the fund was set up, and the eligibility criteria were established, at the initiative of the funding agencies largely without the involvement or lobbying of MFIs.[14]

It is clear that MFIs did not manipulate total assets or average loan size to meet the program criteria before the Rating Fund was announced. This alternative approach, however, only allows us to make use of variation in the December 2000 data. This has two implications. First, we are restricted to analyzing only those MFIs that existed in the data in December 2000. Second, the December 2000 data will only serve as a reasonable proxy for eligibility for a short window around the initiation of the Rating Fund. We analyze a three-year window from December 2000 to December 2003.

We begin by testing the instrument. We estimate (6) in the loan-level data using total assets and average loan size values in December 2000. (The regression includes the usual controls including year and MFI fixed effects). As shown in the first column of Table 6, MFIs that met the eligibility criteria just before the Rating Fund was announced are significantly (t-stat=1.68) more likely to be evaluated after its inception. An eligible MFI has a probability of being evaluated that is 0.242 higher than a non-eligible MFI. This first-stage result supports the use of the eligibility in December 2000 instrument.

We then consider the impact of evaluations on interest rates. We re-estimate the interest rate regression (including loan characteristic controls and MFI-lender pair effects) and find that evaluations (instrumented by the prior eligibility) significantly (t-

[13] We thank an anonymous referee for this suggestion.

[14] Our interviews with Rating Fund officials and experts clearly indicated that the launching of the Rating Fund was external to the action of MFIs.

stat=-3.59) reduce the rate paid by the MFI, as shown in the second column of Table 6. For this specification, we find that an evaluation reduces the rate by 0.093, an even larger effect than we found in the base specification.

The prior eligibility instrument significantly (t-stat=4.06) predicts evaluations in the MFI-level analysis as well, as displayed in the third column of Table 6. With respect to the quantity of financing, the evidence using this instrument is mixed: short-term debt over assets is estimated to decline after an evaluation, while demand deposits over assets shows no significant change (results shown in the fourth and fifth columns of Table 6, respectively). In untabulated results, we find that evaluations decrease the ratio of long-term debt to assets. Taken together with the insignificant debt findings and the positive demand deposit result in Table 5, the evidence on the effects of evaluations on the supply of finance is weak and mixed.

Using prior eligibility as an instrument, we show in column six of Table 6 that the impact of evaluations on the number of clients is positive and significant (t-stat=1.69). The ratio of Clients per Credit Officer also significantly increases (t-stat=4.92) after an evaluation, as described in Table 6, column 7. This provides additional support to the finding in Table 5 and suggests that operational efficiency does improve after an MFI is placed under the additional scrutiny of evaluations. Overall, the results from the previous eligibility instrument support the argument that the Rating Fund subsidy encouraged evaluations and that these evaluations led to less expensive credit and more efficient operations by MFIs.

4.6 Evaluations and MFI Outreach

The evidence discussed above makes clear that evaluations reduce the costs of financing for MFIs and lead them to make loans in a more efficient manner. One central issue in the study of microfinance, however, is the tension between a purely financial assessment of MFIs as lending institutions and an appraisal of the broader social function of MFIs in relieving poverty. The results in Sections 4.2, 4.4 and 4.5 support the argument that evaluations improve the financial viability of MFIs. The larger concern underlying donors and social investors' support for initiatives like the Rating Fund subsidy, however, is that MFIs play a role in poverty reduction.

One central measure of the social effectiveness of an MFI is the extent of its outreach efforts in lending to poorer borrowers. A typical measure of this outreach is the average size of a loan extended by the MFI. MFIs with smaller average loan sizes are typically judged to be better serving the least wealthy sector of society. While evaluations may reduce the cost of finance for MFIs and encourage them to operate more efficiently, evaluations may also drive MFIs to focus more on profitability and to neglect their social missions. In particular, MFIs may make fewer small loans to poor clients.

Our primary regression discontinuity 2SLS approach that exploits contemporaneous eligibility is ill-suited for testing the outreach conjecture. Following the Rating Fund eligibility criteria, that empirical design uses an MFI's transition from having an average loan size above \$2,000 to having an average loan size below \$2,000 as one of the three discontinuities associated with a higher evaluation probability. In other words, the regression discontinuity approach mechanically induces a correlation between the instrument for being evaluated and an MFI's average loan size.

The alternative specification using previous eligibility that we described in Section 4.5, however, does not suffer from this problem as the instrument is not determined by subsequent changes in average loan size. The results in Table 6 establish that previous eligibility predicts future evaluations (column one of Table 7 repeats the third column of 6 for clarity of presentation). In the second column of Table 7, we display the results from the regression of future average loan size expressed in logs on evaluation (instrumented via eligibility in December 2000). Average loan size is unaffected (t-stat=0.02) following an evaluation.

Our findings contribute to the study of the institutional mechanisms that encourage the integration of global capital markets. An important body of research has studied the gradual integration of equities in emerging economies into the world stock market (e.g., Bekaert and Harvey (1995), de Jong and de Roon (2005)). Less attention has been paid to the integration of global banking markets. Our results suggest that rating agency evaluations can play a central role in granting MFIs (an important source of financing in many developing economies) less costly access worldwide commercial sources of credit, without impairing their social function.

4.7 Costs and Benefits of the Rating Fund Subsidy

The evidence we have presented suggests that the Rating Fund subsidy brought large benefits to participating MFIs, as subsidized evaluations led to significantly less expensive financing and improved operating efficiency. Though we do not have the market value information that would allow for a precise quantification, the MFIs that received the subsidy appear to have experienced important gains. In fact, it is reasonable to ask, given the scale of the benefits and the moderate size of the subsidy, why MFIs did not simply seek evaluations on their own, prior to the opening of the Rating Fund.

We think three points help to explain the importance of the Rating Fund. First, the advantages of evaluations may simply not have been well-known ex ante. MFIs may not have had enough information to correctly surmise that evaluations could be very useful. By subsidizing 80% of the cost of the first evaluation, the Rating Fund essentially removed most downside risk for the MFIs and thereby encouraged them to proceed.[15] Second, there were likely some unobserved costs of incentivizing MFIs. The Rating Fund incurred additional expenses to make MFIs aware of the existence of the subsidy (e.g.,

[15]In support of this argument, Meloni and Suaznábar (2005) show that MFIs were particularly likely to use the Rating Fund to support first reports, as opposed to updates. That is, the Rating Fund apparently was most helpful in establishing the value of ratings for MFIs that had not used them before. In general, the net benefits of microfinance are difficult to forecast ex ante (Kaboski and Townsend (2008)).

advertising and marketing of the Fund). These transaction costs (including search and education costs) were not internalized by MFIs but rather by the Rating Fund. It is, therefore, reasonable to believe that the subsidy may have really amounted to more than 100% of the list price of an evaluation when those transaction costs are added to the nominal subsidy. Last, it is worthwhile to note that for it to be effective, the subsidy need only have influence at the margin. In their (unobserved) cost-benefit analysis, MFIs may have been barely averse or indifferent to pursuing evaluations by themselves. The absolute value of the subsidy, therefore, is not the central issue; the question is whether we observe a change in marginal behavior triggered by the incentive, which we do.

5 Conclusion

In this paper we provide direct evidence on the effects of asymmetric information on both financing and operating efficiency by analyzing the impact of credit evaluations in the microfinance industry. Evaluations reduce information asymmetries but seeking an evaluation is, in general, an endogenous choice for a firm. We exploit a targeted subsidy offered by the non-profit Rating Fund and make use of a regression discontinuity design to measure the impact of an exogenous decrease in the asymmetric information about a given MFI. We first show that subsidized MFIs are more likely to receive an evaluation. Using an instrumenting approach, we then demonstrate in a loan-level analysis that evaluations lead to much lower financing costs. These benefits are particularly large for MFIs that borrow from commercial lenders and in short-term MFI-lender relationships. Evaluations do not, however, generate more funding to MFIs. In a study of the operational effects of evaluations, we find that evaluated MFIs invest more efficiently: they have higher client to credit officer ratios. Our main findings are confirmed in a second specification in which we use an MFI's eligibility for the Rating Fund prior to its announcement as an instrument for evaluation. Further, we show that evaluated MFIs do not originate larger loans on average, which we interpret to show that evaluations do not diminish the social impact of MFIs.

Asymmetric information can lead to distorted investment strategies within firms. We provide evidence that credit evaluations, and the accompanying capital market discipline, can have a significant effect on MFIs. Evaluations lead MFIs to make better use of the human resources of their credit officers. More broadly, this suggests that financial market scrutiny may lead to more productive and successful investment by firms. In terms of real consequences, the impact of asymmetric information in facilitating investment inefficiencies may be as important as its effect in hindering the provision of finance.

Taken together, our findings suggest that credit evaluations are a simple and inexpensive mechanism for reducing credit costs for microfinance and for bringing it into the mainstream of the worldwide financial institution industry. Evaluations hold the promise of linking some of the world's neediest borrowers to the rich resources of global capital markets.

References

Acharya, Viral, and Timothy Johnson, 2007, Insider trading in credit derivatives, *Journal of Financial Economics* 84, 110–141.

Ahlin, Christian, and Jocelyn Lin, 2006, Luck or skill? MFI performance in the macroeconomic context, Working Paper.

Armendariz de Aghion, Beatriz, and Jonathan Morduch, 2005, *The Economics of Microfinance* (MIT Press).

Bekaert, Geert, and Campbell R. Harvey, 1995, Time-varying world market integration, *Journal of Finance* 50, 403–444.

Bernardo, Antonio E., Hongbin Cai, and Jiang Luo, 2004, Capital budgeting in multidivision firms: Information, agency, and incentives, *Review of Financial Studies* 17, 739–767.

Brau, James, and Gary Woller, 2004, Microfinance: A comprehensive review of the existing literature, *Journal of Entrepreneurial Finance and Business Ventures* 9, 1–26.

Bubna, Amit, and Bhagwan Chowdhry, 2007, Franchising microfinance, Working Paper.

Cantor, Richard, 2004, An introduction to recent research on credit ratings, *Journal of Banking and Finance* 28, 2565–2573.

Card, David, Carlos Dobkin, and Nicole Maestas, 2004, The impact of nearly universal insurance coverage on health care utilization and health: Evidence from Medicare, NBER working paper.

Chiappori, Pierre-André, and Bernard Salanié, 2000, Testing for asymmetric information in insurance markets, *Journal of Political Economy* 108, 56–78.

Consultative Group to Assist the Poor, 2004a, Financial institutions with a "double bottom line": Implications for the future of microfinance, CGAP Occasional Paper 8.

——— , 2004b, Foreign investment in microfinance: Debt and equity from quasi-commercial investors, CGAP Focus Note 25.

Cull, Robert, Asli Demirguç-Künt, and Jonathan Morduch, 2007, Financial performance and outreach: A global analysis of leading microbanks, *Economic Journal* 117, F107–F133.

de Jong, Frank, and Frans A. de Roon, 2005, Time-varying market integration and expected returns in emerging markets, *Journal of Financial Economics* 78, 583–613.

de Mel, Suresh, David McKenzie, and Christopher Woodruff, 2008, Returns to capital in microenterprises: Evidence from a field experiment, *Quarterly Journal of Economics* 123, 1329–1372.

Dorado, Silvia, and Rick Molz, 2005, Co-evolution of boards of directors in microfinance organizations: The case of BancoSol and Los Andes, *Journal of Developmental Entrepreneurship* 10, 99–121.

Faulkender, Michael, and Mitchell A. Petersen, 2006, Does the source of capital affect capital structure?, *Review of Financial Studies* 19, 45–79.

Garmaise, Mark J., and Tobias J. Moskowitz, 2004, Confronting information asymmetries: Evidence from real estate markets, *Review of Financial Studies* 17, 405–437.

Giné, Xavier, and Dean S. Karlan, 2008, Peer monitoring and enforcement: Long term evidence from microcredit lending groups with and without group liability, Yale University working paper.

Giné, Xavier, Robert Townsend, and James Vickery, 2007, Patterns of rainfall insurance participation in rural India, World Bank Policy Research Working Paper 4408.

Gutierrez-Nieto, Begoña, and Carlos Serrano-Cinca, 2007, Factors explaining the rating of microfinance institutions, *Nonprofit and Voluntary Sector Quarterly* 36, 439–464.

Hahn, Jinyong, Petra Todd, and Wilbert Van der Klaauw, 2001, Identification and estimation of treatment effects with a regression-discontinuity design, *Econometrica* 69, 201–209.

Hartarska, Valentina, and Denis Nadolnyak, 2008, Does rating help microfinance institutions raise funds? Cross-country evidence, *International Review of Economics and Finance* forthcoming.

Hertzberg, Andrew, Jose Maria Liberti, and Daniel Paravisini, 2008, Public information and coordination: Evidence from a credit registry expansion, Columbia University working paper.

Isern, Jennifer, Julie Abrams, and Matthew Brown, 2008, Appraisal guide for microfinance institutions, CGAP Resource Manual.

Jansson, Tor, 2003, Financing microfinance, Inter-American Development Bank.

Johnston, Don, and Jonathan Morduch, 2007, Microcredit vs. microsaving: Evidence from Indonesia, New York University working paper.

Kaboski, Joseph P., and Robert M. Townsend, 2008, A structural evaluation of a large-scale quasi-experimental microfinance initiative, MIT working paper.

Karlan, Dean S., 2005, Using experimental economics to measure social capital and predict financial decisions, *American Economic Review* 95, 1688–1699.

———, and Jonathan Zinman, 2008, Observing unobservables: Identifying information asymmetries with a consumer credit field experiment, *Econometrica* forthcoming.

———, 2009, Expanding credit access: Using randomized supply decisions to estimate the impacts, *Review of Financial Studies* forthcoming.

Khandker, Shahidur R., 2005, Microfinance and poverty: Evidence using panel data from Bangladesh, *World Bank Economic Review* 19, 263–286.

Kisgen, Darren J., 2006, Credit Ratings and Capital Structure, *Journal of Finance* 61, 1035–1073.

Lee, David S., 2008, Randomized experiments from non-random selection in U.S. house elections, *Journal of Econometrics* 142, 675–697.

Loubière, Jacques Trigo, Patricia Lee Devaney, and Elisabeth Rhyne, 2004, Supervising and regulating microfinance in the context of financial sector liberalization: Lessons from Bolivia, Colombia and Mexico, Report to the Tinker Foundation.

Marino, Anthony M., and John G. Matsusaka, 2005, Decision processes, agency problems, and information: An economic analysis of capital budgeting procedures, *Review of Financial Studies* 18, 301–325.

Matsudaira, Jordan D., 2008, Mandatory summer school and student achievement, *Journal of Econometrics* 142, 829–850.

MATTHÄUS-MAIER, INGRID., AND J.D. VON PISCHKE (eds.), 2006, *Microfinance Investment Funds: Leveraging Private Capital for Economic Growth and Poverty Reduction* (Springer).

McIntosh, Craig, Gonzalo Villaran, and Bruce Wydick, 2008, Microfinance and home improvement: Using retrospective panel data to measure program effects on fundamental events, University of California, San Diego working paper.

McKim, Andrew, and Matthew Hughart, 2005, Staff incentive schemes in practice: Findings from a global survey of microfinance institutions, CGAP working paper.

Meloni, Caterina, and Claudia Suaznábar, 2005, Key data on the MF rating industry and the Rating Fund, Rating Fund working paper.

Morduch, Jonathan, 1999, The microfinance promise, *Journal of Economic Literature* 37, 1569–1614.

——— , 2000, The microfinance schism, *World Development* 28, 617–629.

Odders-White, Elizabeth R., and Mark J. Ready, 2006, Credit ratings and stock liquidity, *Review of Financial Studies* 19, 119–157.

Petersen, Mitchell A., and Raghuram G. Rajan, 1994, The benefits of lending relationships: Evidence from small business data, *Journal of Finance* 49, 3–37.

———, 2002, Does distance still matter? The information revolution in small business lending, *Journal of Finance* 57, 2533–2570.

Rajan, Raghuram G., 1992, Insiders and outsiders: The choice between informed and arm's-length debt, *Journal of Finance* 47, 1367–1400.

Sharpe, Steven A., 1990, Asymmetric information, bank lending and implicit contracts: A stylized model of customer relationships, *Journal of Finance* 45, 1069–1087.

Skreta, Vasiliki, and Laura Veldkamp, 2009, Ratings shopping and asset complexity: A theory of ratings inflation, *Journal of Monetary Economics* forthcoming.

Ssendi, Lucy, and Alistair R. Anderson, 2009, Tanzanian micro enterprises and micro finance: The role and impact for poor rural women, *Journal of Entrepreneurship* 18, 1–19.

Stauffenberg, Damian Von, and Julie Abrams, 2007, Role reversal: Are public development institutions crowding out private investment in microfinance?, MicroRate report.

Sufi, Amir, 2009, The real effects of debt certification: Evidence from the introduction of bank loan ratings, *Review of Financial Studies* 22, 1659–1691.

———, and Michael R. Roberts, 2009, Control rights and capital structure: An empirical investigation, *Journal of Finance* forthcoming.

Tang, Tony, 2009, Information asymmetry and firms credit market access: Evidence from Moody's credit rating format refinement, *Journal of Financial Economics* forthcoming.

Figure 1: The Operation and Investment of Microfinance Institutions

This figure shows the average number of clients per MFI in the sample, and the average portfolio of loans extended per MFI in the period studied, expressed in millions of dollars.

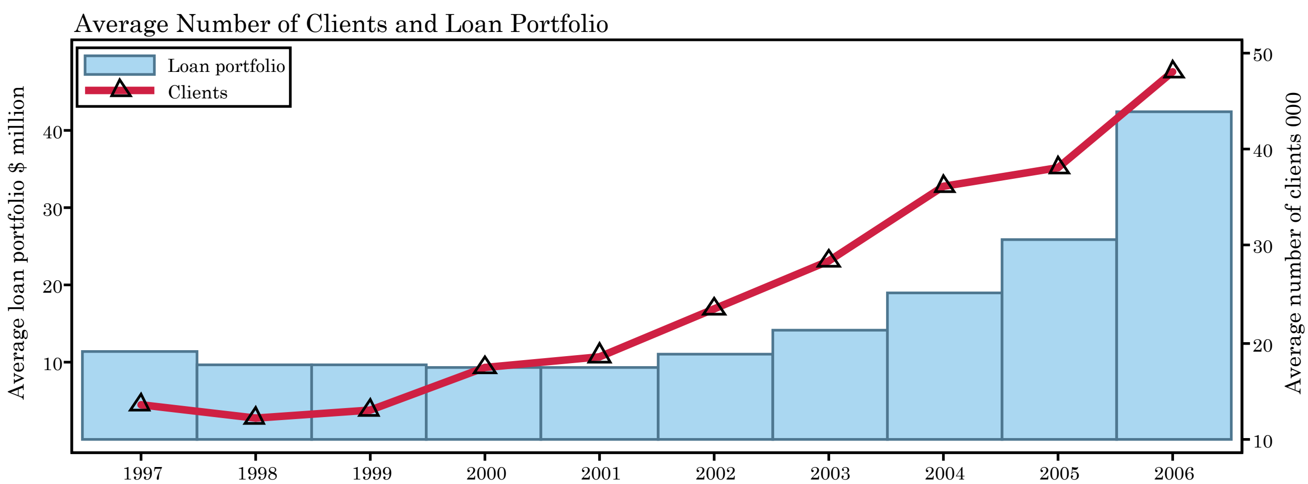

Figure 2: The Funding of Microfinance Institutions

This figure shows the average funding received by MFIs from non-commercial lenders (i.e., government, development banks, NGOs, cooperatives, and other MFIs) and commercial lenders (i.e., commercial funds, global banks, and local banks) in the period studied.

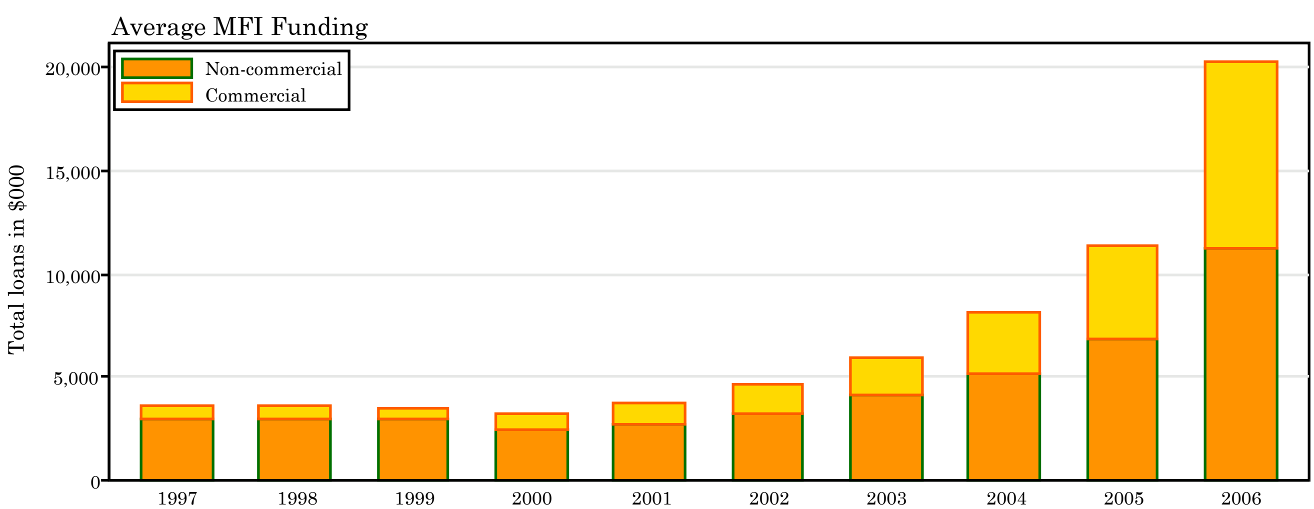

Figure 3: Interest Rate and Asset Size around Eligibility Border

This figure shows the average interest rate paid by MFIs on their total loans outstanding and their asset size in millions of dollars around the eligibility border defined in equation (3), plotting actual and linearly fitted values.

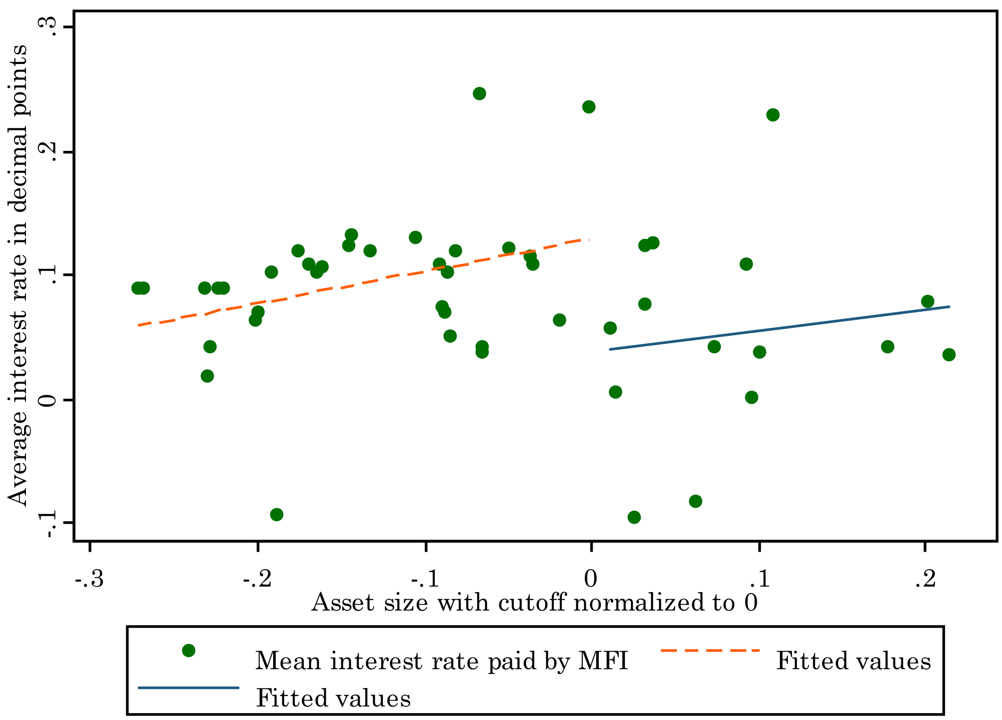

Table 1: Summary Statistics

The data are from MicroRate. The unit of observation is a microfinance institution (MFI) at a given period, mostly end of semester. Evaluation is a dummy indicating whether MicroRate performed an evaluation of the MFI. Eligibility is the interaction of two variables: whether the Rating fund is active (May 2001 onwards), and whether the MFI complies with the two size requirements for the subsidy: assets between $0.5M and $30M (Latin America) or $0.3M and $30M (rest of the world), and an average loan size of less than $3K (Latin America) or less than $2K (rest of the world). Dollar amounts are in $000 and expressed in logarithms. The weighted average interest rate is calculated over all loans outstanding in the liabilities of the MFI at the end of period. Cash and cash equivalents is a ratio over assets. Fixed property and long term investments is a ratio over assets. Average loan size refers to the loans made by MFIs to their clients. Portfolio quality is the fraction of the portfolio composed of loans with less than 30 days past due; leverage is total liabilities over total equity; demand deposits are expressed as a ratio over total assets; long term debt is expressed as a ratio over assets; credit staff is expressed as a ratio over total staff of the MFI.

Variable	**Median**	**Mean**	**Std.Dev.**	**Min.**	**Max.**	**n**
Evaluation (0/1)	0.00	0.24	0.43	0.00	1.00	1380
Eligibility dummy	1.00	0.52	0.50	0.00	1.00	1380
Required size dummy	1.00	0.66	0.47	0.00	1.00	1380
Rating fund period dummy	1.00	0.81	0.39	0.00	1.00	1380
$ All Loans received (log)	8.11	7.94	1.71	0.65	12.10	1094
Weighted averaged interest rate	0.08	0.08	0.06	-0.30	0.40	1094
Cash and cash equivalents	0.08	0.10	0.10	0.00	0.71	1380
Portfolio (in $M)	4.67	18.51	39.49	0.00	463.00	1380
Fixed property and LT investments	0.04	0.05	0.04	0.00	0.44	1376
Number of clients (log)	9.65	9.53	1.36	4.55	13.83	1274
Clients per credit officer	292.04	333.73	380.33	0.00	6234.53	1310
Average loan size (in $000)	0.59	2.55	52.02	0.00	1801.29	1296
Portfolio quality	0.95	0.85	0.28	0.00	1.00	1326
Leverage	2.07	2.35	2.04	0.00	27.83	1360
Demand deposits	0.00	0.08	0.15	0.00	0.92	1380
Long term debt	0.26	0.27	0.21	0.00	1.66	1380
Credit staff	0.44	0.45	0.13	0.03	0.91	1309

Table 2: Triple Discontinuity in MFI Characteristics and Evaluations

The table presents regression discontinuity models of MFI evaluations. The unit of observation is an MFI at a given period, mostly end of semester. Evaluation is a dummy indicating whether MicroRate performed an evaluation of the MFI. Model 1 includes polynomials of fourth degree, whereas model 2 includes polynomials of fifth degree. The controls are leverage, demand deposits, credit staff, and an unreported constant. t-statistics for heteroskedasticity-robust standard errors clustered by MFI are in parentheses.

	Dependent Variable: **MFI evaluated (1/0)**	
	OLS	OLS
	(2.1)	(2.2)
Asset jump × Loan Size jump × CGAP jump	0.311***	0.311***
	(3.72)	(3.75)
Asset jump (dummy)	Yes	Yes
Loan size jump (dummy)	Yes	Yes
CGAP jump (dummy)	Yes	Yes
Asset jump × Loan size jump	Yes	Yes
Asset jump × CGAP jump	Yes	Yes
Loan size jump × CGAP jump	Yes	Yes
4th-degree polynomial Assets	Yes	Yes
4th-degree polynomial Loan Size	Yes	Yes
4th-degree poynomial interacted with Jumps	Yes	Yes
5th-degree polynomial Assets	No	Yes
5th-degree polynomial Loan Size	No	Yes
5th-degree poynomial interacted with Jumps	No	Yes
MFI controls (dem.deposits, leverage, credit staff)	Yes	Yes
Fixed effects:		
MFI	Yes	Yes
Year	Yes	Yes
n	925	925
N clusters	124	124

***, **,* are 1%, 5% and 10% levels, respectively.

Standard errors are heteroskedasticity-robust and clustered by MFI.

Table 3: Evaluations and Financing Terms

The table presents regression-discontinuity instrumental variable models of how evaluations affect the pricing of loans obtained by MFIs. The unit of observation is a loan outstanding in the liabilities of the MFI. The dependent variable is the interest rate of the loan expressed in dollars using the forward exchange rate from Datastream (World Markets / Reuters) whenever available, or the perfect forecasting factor using realized future exchange rates. The age of the MFI is measured in years. The relationship between the lender and the MFI is measured as the cumulative count of semesters in which they had loans outstanding. The loan-level controls include loan amount in logarithms, loan maturity, currency, as well as an unreported constant. Fixed effects for each MFI-lender pair and for each year are included. t-statistics for heteroskedasticity-robust standard errors clustered by MFI are in parentheses.

	Dependent Variable: **Interest rate in decimal points**		
	OLS	RD-2SLS* 1st Stage	RD-2SLS* 2nd Stage
	(3.1)	(3.2)	(3.3)
Evaluation$_{t-1}$	−0.012		
	(−1.56)		
Evaluation$_{t-1}$ (Instrumented)			−0.055**
			(−2.52)
(Asset jump × Loan Size jump × CGAP jump)$_{t-1}$		0.365*	
		(1.95)	
Loan amount (log)	0.002		0.002
	(1.63)		(1.40)
Loan is in U.S. currency	−0.016**		−0.014
	(−2.38)		(−1.25)
Loan is short term	0.002		0.003
	(0.95)		(1.19)
Relationship	0.002**		0.006
	(2.06)		(1.52)
Age of MFI	0.002***		0.002
	(4.04)		(0.85)
Asset jump (dummy)$_{t-1}$	No	Yes	Yes
Loan size jump (dummy)$_{t-1}$	No	Yes	Yes
CGAP jump (dummy)$_{t-1}$	No	Yes	Yes
(Asset jump × Loan size jump)$_{t-1}$	No	Yes	Yes
(Asset jump × CGAP jump)$_{t-1}$	No	Yes	Yes
(Loan size jump × CGAP jump)$_{t-1}$	No	Yes	Yes
4th-degree polyn. Assets$_{t-1}$	No	Yes	Yes
4th-degree polyn. Loan Size$_{t-1}$	No	Yes	Yes
(4th-degree pol. interacted with Jumps)$_{t-1}$	No	Yes	Yes
MFI-Lender Pair fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
n	10665	6322	6322
N clusters	114	105	105

***, **,* are 1%, 5% and 10% levels. Std. errors for t-stats. are heteroskedasticity-robust and clustered by MFI.
2SLS* models in this table omit loan-level variables in the 1st stage because they are posterior to $Evaluation_{t-1}$.

Table 4: Evaluations, Financing Terms, and Cross-Sectional Characteristics

The table presents regression-discontinuity instrumental variable models of how evaluations affect the pricing of loans obtained by MFIs. The unit of observation is a loan outstanding in the liabilities of the MFI. The dependent variable is the interest rate of the loan expressed in dollars using the forward exchange rate from Datastream (World Markets / Reuters) whenever available, or the perfect forecasting factor using realized future exchange rates. The first panel classifies *lenders* as commercial if they are global banks, global commercial funds, or local banks. The second panel classifies MFIs depending on their age. The third panel classifies loan *relationships* using a cumulative count of five semesters as the cutoff. The loan-level controls include loan amount in logarithms, loan maturity, currency, as well as an unreported constant. Fixed effects for each MFI-lender pair and for each year are included. t-statistics for heteroskedasticity-robust standard errors clustered by MFI are in parentheses.

	Dependent Variable: **Interest rate in decimal points**					
	RD-2SLS* 2nd stage		RD-2SLS* 2nd stage		RD-2SLS* 2nd stage	
	Commercial lenders		**MFIs founded before 1997**		**Long Relationships**	
	No	Yes	No	Yes	No	Yes
	(4.1)	(4.2)	(4.3)	(4.4)	(4.5)	(4.6)
Evaluation$_{t-1}$ (Instrumented)	−0.042**	−0.190**	−0.000	−0.061**	−0.102**	0.0
	(−2.34)	(−2.30)	(−0.01)	(−2.11)	(−2.41)	(0.02)
Loan level controls	Yes	Yes	Yes	Yes	Yes	Yes
Assets, Loan size, CGAP jumps (dummies)$_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes
(Asset jump × Loan size jump)$_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes
(Asset jump × CGAP jump)$_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes
(Loan size jump × CGAP jump)$_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes
(4th-degree polyn.of Assets and Loan Size)$_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes
(4th-degree pol. interacted with Jumps)$_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes
MFI-Lender Pair fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
n	4569	1753	2308	4014	4665	1657
N clusters	101	78	43	62	105	51

***, **,* are 1%, 5% and 10% levels. Std. errors for t-stats. are heteroskedasticity-robust and clustered by MFI.
2SLS* models in this table omit loan-level variables in the 1st stage because they are posterior to $Evaluation_{t-1}$.

Table 5: Evaluations, Financing and Real Consequences

The table presents regression-discontinuity instrumental variable models of how evaluations affect financing and operating variables two periods into the future. The unit of observation is an MFI at a given period, mostly end of semester. The first stage for all models is in column 1 of table 2. Short term debt, long term debt , and demand deposits are expressed as a ratio over assets. The number of clients of an MFI is expressed in thousands and logged. MFI-level controls include leverage, demand deposits, and credit staff, as well as an unreported constant. t-statistics for heteroskedasticity-robust standard errors clustered by MFI are in parentheses.

Dependent Variable:	**Short-term Debt**	**Long-term Debt**	**Demand Deposits**	**# Clients**	**Clients per Credit Officer**
	RD-2SLS 2nd stage (5.1)	RD-2SLS 2nd stage (5.2)	RD-2SLS 2nd stage (5.3)	RD-2SLS 2nd stage (5.4)	RD-2SLS 2nd stage (5.5)
Evaluation (Instrumented)	−0.001	−0.075	0.057***	0.412**	151.594**
	(−0.02)	(−1.17)	(3.18)	(2.37)	(2.03)
Leverage	0.005**	0.011**	−0.002	−0.013	2.066
	(2.22)	(2.36)	(−0.79)	(−1.60)	(0.82)
Demand Deposits	0.358***	−0.528***	0.598***	−0.511	−36.113
	(3.19)	(−4.11)	(3.50)	(−1.50)	(−0.16)
Credit staff	0.059	−0.052	−0.033	−0.007	−238.466***
	(0.68)	(−0.56)	(−1.58)	(−0.03)	(−3.62)
Asset jump (dummy)	Yes	Yes	Yes	Yes	Yes
Loan size jump (dummy)	Yes	Yes	Yes	Yes	Yes
CGAP jump (dummy)	Yes	Yes	Yes	Yes	Yes
Asset jump × Loan size jump	Yes	Yes	Yes	Yes	Yes
Asset jump × CGAP jump	Yes	Yes	Yes	Yes	Yes
Loan size jump × CGAP jump	Yes	Yes	Yes	Yes	Yes
4th-degree polyn. Assets	Yes	Yes	Yes	Yes	Yes
4th-degree polyn. Loan Size	Yes	Yes	Yes	Yes	Yes
4th-degree pol. interacted with Jumps	Yes	Yes	Yes	Yes	Yes
Fixed effects:					
MFI	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
n	771	771	771	735	766
N clusters	117	117	117	116	117

***, **,* are 1%, 5% and 10% levels, respectively. Standard errors are heteroskedasticity-robust and clustered by MFI.

Table 6: Robustness: Eligibility Prior to the Rating Fund

The table replicates the primary regression-discontinuity instrumental variable models of how evaluations affect financing and operating variables two periods into the future, with two differences: (i) the asset size and loan size values imputed for equations (5) and (6) are those of December 2000 (or the latest period in 2000), that is, before the Rating Fund was announced; (ii) the period for the analysis is shortened to a narrow window around the introduction of the Rating Fund, that is, from the second semester of 2000 to the second semester of 2003. Note that the number of MFIs drops to those just affected at the moment of the introduction of the Rating Fund, that is, those present in the data in 2000 for which information is available. All specifications (i.e., lags, interactions, polynomials, controls, and fixed effects) are as before. t-statistics for heteroskedasticity-robust standard errors clustered by MFI are in parentheses.

	Loan-level analysis		MFI-level analysis				
Dependent Variable:	**Evaluation (1/0)** RD-2SLS* 1st stage (6.1)	**Interest Rate in decimal points** RD-2SLS* 2nd stage (6.2)	**Evaluation (1/0)** RD-2SLS 1st stage (6.3)	**Short-term Debt** RD-2SLS 2nd stage (6.4)	**Demand Deposits** RD-2SLS 2nd stage (6.5)	**#Clients** RD-2SLS 2nd stage (6.6)	**Clients per Credit Officer** RD-2SLS 2nd stage (6.7)
Asset $\text{jump}_{2000} \times$ Loan Size $\text{jump}_{2000} \times$ CGAP jump	0.242*		0.702***				
	(1.68)		(4.06)				
Evaluation (Instrumented)		−0.093***		−0.111***	0.003	0.127*	115.008***
		(−3.59)		(−5.81)	(0.90)	(1.69)	(4.92)
n	2026	2026	269	253	253	246	252
N clusters	49	49	55	55	55	55	55

***, **,* are 1%, 5% and 10% levels, respectively. Standard errors are heteroskedasticity-robust and clustered by MFI.

Table 7: Outreach Consequences of Information and Financing

The table shows how evaluations affect average loan size two periods into the future, replicating the primary specification with two differences: (i) the asset size and loan size values imputed for equations (5) and (6) are those of December 2000 (or the latest period in 2000), that is, before the Rating Fund was announced; (ii) the period for the analysis is shortened to a narrow window around the introduction of the Rating Fund, that is, from the second semester of 2000 to the second semester of 2003. Note that the number of MFIs drops to those just affected at the moment of the introduction of the Rating Fund, that is, those present in the data in 2000. t-statistics for heteroskedasticity-robust standard errors clustered by MFI are in parentheses.

	Dependent Variable:	
	Evaluation (1/0)	**Average Loan Size**
	RD-2SLS 1st stage (7.1)	RD-2SLS 2nd stage (7.2)
Asset jump$_{2000}\times$ Loan Size jump$_{2000}\times$ CGAP jump	0.702***	
	(4.06)	
Evaluation (Instrumented)		0.001
		(0.02)
Leverage	−0.013	0.025
	(−0.70)	(0.95)
Demand Deposits	−0.043	−0.521
	(−0.08)	(−1.64)
Credit staff	0.902	−0.061
	(1.20)	(−0.23)
Asset jump$_{2000}$ (dummy)	Yes	Yes
Loan size jump$_{2000}$ (dummy)	Yes	Yes
CGAP jump (dummy)	Yes	Yes
Asset jump$_{2000}\times$ Loan size jump$_{2000}$	Yes	Yes
Asset jump$_{2000}\times$ CGAP jump	Yes	Yes
Loan size jump$_{2000}\times$ CGAP jump	Yes	Yes
4th-degree polyn. Assets	Yes	Yes
4th-degree polyn. Loan Size	Yes	Yes
4th-degree pol. interacted with Jumps	Yes	Yes
Fixed effects:		
MFI	Yes	Yes
Year	Yes	Yes
n	269	247
N clusters	55	54

**,* are 5% and 10% levels of two-tailed tests.

t-statistics use robust standard errors clustered by MFI.