WOMEN'S WORLD BANKING
WHAT WORKS

CREDIT SCORING IN MICROFINANCE

GUIDELINES BASED ON EXPERIENCE WITH WWB AFFILIATES IN COLOMBIA AND THE DOMINICAN REPUBLIC

INTRODUCTION

This WWB What Works note is based on the results of the WWB Loan Scoring Project in progress in ADOPEM of the Dominican Republic and in the five WWB affiliates in Colombia: FWWB-Cali; FMM-Popayán; CMM-Medellín; CMM-Bogotá and FMM-Bucaramanga. WWB global team members have worked closely with the senior managers of these institutions on the design and implementation of this project. Credit managers and loan officers have contributed their field experience to the construction of the loan scoring model and the design of the implementation process.

Leading microfinance institutions (MFIs) in the Latin America/Caribbean region are setting performance standards that would have been difficult to imagine ten years ago. In institutions such as FWWB-Cali and FMM-Popayán in Colombia and Caja los Andes in Bolivia, productivity increased dramatically in the last decade, from 250 to more than 500 loans outstanding per loan officer, reducing the level of operational costs as a share of average portfolio from 35% to as low as 15%.

Some MFIs have achieved these results by increasing the average loan size from US$400 to more than US$1,000. Loan size increases have been more pronounced in the institutions that have become formalized and are regulated, such as Financiera Calpia and Caja los Andes. In contrast, in WWB affiliates in Colombia and the Dominican Republic, average loan sizes have remained relatively small, well below the US$400 level.

A number of institutions, including FWWB-Cali and FMM-Popayán, have reached the "productivity frontier" of their existing lending methodology. They are at the upper threshold of efficiency that can be achieved with the systems they currently use. It is difficult to imagine how these institutions could achieve further improvements in loan officer productivity from the current high levels of 600 active loans per loan officer.

During the Bolivian microfinance crisis of 1999, it became evident that leading MFIs were operating at caseloads in excess of their loan officers' capacities. The crisis forced MFIs to reduce the load of loan officers, to allow them to manage arrears. To maintain the same levels of cost efficiency, many MFIs resorted to larger loan sizes, thus moving into new market niches at the expense of smaller microenterprise clients. The experience in Bolivia represents a common trend among MFIs facing the limits of their productivity frontier: the search for greater efficiency through larger case loads, and subsequently higher arrears and larger loan sizes. WWB affiliates in Colombia and the Dominican Republic have experienced no such erosion in portfolio quality and have continued to focus on serving low income clients with relatively small loans.

MFIs that strive to provide quality financial services to the poor must investigate innovations that enable them to continue increasing efficiency without moving from their mission and target client base. New efforts have been undertaken to seek technological innovations that push out the productivity frontier but do not overload loan officers or squeeze out low income clients. Rather, these innovations introduce and integrate technologies such as credit scoring and palm pilots. These techniques can improve loan officer productivity and reduce transaction costs for the institution.

1. WHAT IS CREDIT SCORING?

Traditionally, MFIs have used subjective scoring—the use of defined parameters such as experience in the business, net margin of the business, profitability and disposable income—to analyze businesses and credit risk. These parameters are defined using industry standards, institutional experience and stated lending policies. A number of qualitative indicators are also used as selection criteria. Loan officers need a lot of time and training to be able to understand and apply the parameters and policies of subjective scoring.

In contrast, statistical credit scoring forecasts risk based on quantified characteristics recorded in a database. The relationships between risk and client characteristics are expressed as sets of rules in a mathematical formula that forecasts risk as a probability (Schreiner, June 2002). For example, statistical scoring can determine that a seamstress who is renewing a loan has a 12% likelihood of defaulting, or a male, first-time loan applicant who owns a furniture factory has a 22% likelihood of defaulting. Statistical scoring not only tells if the client is risky or not; it also provides an exact measure of the predicted risk. Statistical credit scoring was introduced in high income countries in the mid 1970s as a means of increasing access to financial services by medium and low income client segments. Today, scoring is widely used by credit card companies that use credit histories and other borrower characteristics to automatically approve credit lines without personal contact with applicants.

2. WHY IS CREDIT SCORING OF INTEREST TO MICROFINANCE?

Microlending is a costly endeavor. For institutions that specialize in individual lending, labor intensive methods are used to assess loan applications and monitor defaulters. For large MFIs that are well run and possess adequate databases, scoring can increase efficiency, outreach and sustainability by improving the time allocation of loan officers. Scoring can reduce time spent collecting overdue payments from delinquent borrowers. In large MFIs that specialize in individual lending in Colombia and the Dominican Republic, on average loan officers spend 40% to 50% of their time in collection activities. Scoring can help reduce that time by prioritizing the visits to those borrowers who are more likely to default, leaving loan officers more time to identify and access new customers.

In the future, scoring could not only be used as a tool to improve risk assessment and delinquency monitoring, it could dramatically improve portfolio management for repeat customers. It is important, however, that MFIs who use credit scoring differentiate between new and repeat clients. Credit scoring for new clients should be used only as a complementary tool to better understand and quantify the sources and levels of risk. It is still too risky to replace traditional risk assessment methods with scoring systems, as discussed later in this report.

Once an institution has gathered relevant information on client repayment behavior, lenders can improve their productivity by reducing the frequency of client visits to update the information. Instead of updating client information each time a loan is renewed, client information is renewed every two years, or any time the loan size increases more than 20%. Some lenders in Latin America have clustered old customers with good repayment behavior, classifying them as special customers and granting them easy and fast access to credit lines. Specialized loan officers are assigned to manage 1,000 to 2,000 of those clients. Scoring could help lenders prioritize information-gathering client visits based on their respective predicted risk, rather than pre-determined time periods. By clustering hundreds of clients by their predicted risk, institutions will be able to increase their productivity levels and reduce their operational costs significantly.

Scoring could also be a powerful tool to enable managers to adjust portfolio composition and trends by economic activity based on a desired risk tolerance level. In the near future, scoring could even predict drop out levels by client type, so that lenders know in advance the life cycle of their different types of clients. At the same time, institutions could estimate profit levels by type and stage of life cycle. Lenders could optimize institutional profitability or impact by selecting the ideal composition between very profitable clients and less profitable clients.

All of these possible applications for credit scoring provide incentive to invest time and resources in improving knowledge and expertise of this technology. However, statistical scoring will not replace subjective scoring by loan officers in the near future. There are some weaknesses with the method. First, the future will not always be like the past, and scoring bases its prediction on past events. Changes can occur with time, making the prediction power of the model less accurate. Second, scoring does not capture all relevant client characteristics, especially those related to qualitative aspects of the client that also have a significant importance on associated total risk.

FACTORS TO CONSIDER WHEN AN MFI INTRODUCES SCORING

Experience to date indicates that several factors need to be taken into account when an MFI is considering the use of loan scoring.

1. PRE-REQUISITES

To introduce credit scoring, the institution needs to have a proven lending methodology that is capable of differentiating between lower risk and higher risk clients. As noted, scoring predicts the future based on past behavior. To be able to predict any outcome, the institution needs a database of its clients' characteristics and their past repayment behavior.

In high income countries, lenders have used scoring systems for many years. However, in those countries scoring is applied to clients that have salaried jobs and records in a credit bureau. In such cases, a scorecard with 15 to 20 variables is enough to construct powerful scoring models. In microfinance, however, most clients are self-employed, own small businesses usually in the informal sector, and have neither records of their incomes nor credit history in the local credit bureaus. Moreover, in developing countries if credit bureaus do exist, their outreach is usually limited to commercial banks. The absence of detailed client information means that a typical characteristic in microloan scoring is much less predictive than a typical characteristic in a scoring model in a high-income country. As a result, in microfinance, more variables are required to build a strong model.

It is frequently asked whether scoring models developed for a particular institution can be used in another MFI. Usually client characteristics vary from one institution to the other. Furthermore, lending processes are different among institutions. Therefore, to extrapolate the results of a scorecard from one institution to another is not appropriate.

2. DATA REQUIREMENTS

It is important to gather and store data from clients to construct scorecards, but what characteristics should a microlender collect?

Below is a list of variables that should be collected, including the core set of required characteristics. Most microlenders who make individual loans collect these core variables as part of their traditional evaluation, however, this information is not always stored in the database and in cases where data is stored, it is rarely used for analysis.

To measure the credit risk of a client, the scoring model considers the client's socio-economic characteristics, the characteristics of the loan and the lender characteristics. A detail of each variable group of variables is listed next. Core characteristics are denoted with an asterisk (*).

Client Characteristics

Demographics:

- Gender*
- Year of birth*
- Marital status*
- Last grade completed in school*

Contact Information:

- Phone contact at home (may be a neighbor's phone)*
- Phone contact at business (may be a neighbor's phone)*
- Distance from the business to the office

Household Demographics:

- Number of people age 18 or older (including applicant)
- Number of people age 17 or younger

Household Assets:

- Home tenure (owner, renter, other)
- Year moved to current residence
- Number of rooms
- Housing construction
  - Tin roof (present or absent)
  - Concrete floor
  - Connection to water lines
  - Connection to sewage lines
  - Connection to electricity
- Vehicles that run
- Appliances
  - Refrigerator (present or absent)
  - Gas or electric stove
  - Working color television
- Formal savings account

Scoring may show that clients with fewer assets have greater risk. Many could argue that using scoring institutions might systematically exclude poorer clients. Therefore it is important to highlight that institutions should use scoring to better understand the risks of their different client segments and to adapt processes and policies to mitigate them. Scoring does not change the risk of borrowers; it only improves knowledge of the risk that already exists.

Business Demographics:

- Sector (manufacturing, services, trade)*
- Specific type of business*
- Year started in this specific business*
- Registration (presence or absence)
- Written records (presence or absence)
- Type of locale (store front, mobile, lock box, home based, other)
- Tenure
- Year moved to current locale
- Number of employees

Financial Flows of the Household/Enterprise:

The strength and variability of cash flow is a strong risk predictor.

- Business revenue*
- Household income from salaries*
- Household income from other sources*
- Business expense for goods purchased*
- Business salary expense*
- Other business expenses*
- Other household expenses*
- Monthly installments due on other debts*
- Rent payment

Stock of the Enterprise:

- Total assets*
  - Fixed assets*
  - Inventory*
  - Cash and bank accounts*
- Total liabilities
  - Informal debt*
  - Formal debt*

Repayment Record with the Institution:

The best predictor of future performance is past performance. For each installment due on each loan, lenders should record the date due and the date paid. This will allow the derivation of the following measure of aspects of arrears:

- Longest spell*
- Days of arrears per installment*
- Number of installments paid late*

Other information that generally is not captured by microlenders, but could significantly improve the prediction powers of the model, is provided below.

Credit Bureau Information

Proxies for Personal Character:

- Number of alcoholic drinks per week
- Number of cigarettes per week
- Number of lottery tickets bought per month
- Number of times religious services are attended per month
- Current membership in neighborhood committee or church group (yes/no)
- Participation in ROSCAs (yes/no)
- Amount saved and frequency

Quantified Subjective Judgments:

To screen for qualitative risk, the institution needs to capture and quantify the loan officer's subjective judgment. This would allow scoring to reveal how the probability of being a risky client is linked with subjective judgment. In order to do so, a rating of "below-average, "average" or "above-average" needs to be assigned to the following client features:

- Overall credit risk
- Honesty and transparency of responses
- Quality of references
- Managerial skills
- Business prospects
- Cash flow variability
- Recent investment in the home or business
- Understanding of the rules of the loan contract
- Family relationships and informal support
- Organization and cleanliness of the home and business

Loan Characteristics

- Date application submitted*
- Date loan disbursed*
- Date paid in full*
- Amount requested*
- Amount disbursed*
- Amount of installment*
- Number and frequency of installments*
- Interest rate, fees and commissions*
- Grace period*
- Reschedule status*
- Type of guarantee*

Lender Characteristics

The branch and loan officer strongly influence risk:

- Branch*
- Loan officer*
  - Gender*
  - Year of birth*
  - Marital status*
  - Number of people in household*
  - Last grade completed*

Scoring has the power to reveal the profile of the ideal loan officer if information on simple loan officer characteristics is gathered.

Given enough defaulters, a powerful scorecard can be constructed from the core characteristics (those denoted by an asterisk). A scorecard with all the characteristics listed above would probably predict with 20% to 40% percent better accuracy than a scorecard using only the core characteristics. (WWB Scoring Project, Colombia, Schreiner, 2002).

The initial investment to collect additional client information could be high. Costs include the redesign of paper forms, entering additional data in the system, and the significant and challenging costs related to the modification of an institution's information system.

3. Guidelines on How to Warehouse Better Data

After human resources and adequate lending technologies, information is a microlender's greatest asset. Often, however, formal information systems are weak, having been used primarily for tracking loans. As greater numbers of MFIs introduce electronic databases into their information systems, greater attention must be paid to data quality. Recommendations in this regard follow.

To ensure consistent models and the investment's worth, microlenders need to discuss and clarify the following aspects of data gathering.

Establish consistent definition for type of business. Identify and agree on a list of 50 or so most-common business types. Establish a formal written policy to code each enterprise as one of the 50 business types. Train loan officers and data entry personnel to correctly apply the agreed definitions.

Do not throw away data. It is important to influence institutions to take a different approach regarding the use of their client information, so that it is viewed as a powerful tool that could help managers and staff make better business decisions in the future.

Enter rejected applications into the information system. By gathering information on rejected applications, it may be possible in the future to shorten some field visits and forecast repayment problems or post-visit rejection. In some institutions, loan officers reject 40% to 60% of the cases visited. It is evident that the introduction of an early warning system before the client visit could significantly reduce costs.

Differentiate loan officers who issue the loan from those who monitor it. One of the three most predictive variables is represented by the personal characteristics of the loan officer. However, the loan officer monitoring the loan may not be the same person who screened and issued it, perhaps because the original loan officer left the institution or was assigned to a different branch. When relocation of a loan officer occurs, most MFIs' information systems only record the current loan officer and delete records of any previous loan officers. The elimination of this historical record reduces the predictive power of scoring. To avoid this problem, it is important to add a field to the database that records the screening officer in addition to the current monitoring loan officer.

Record missing values as missing, not as zero. Most institutions do not record missing values properly; they either change blanks to zeros, or invent (inconsistent) codes for missing values. Often missing values are good predictors of higher risk, because they represent a weak or superficial analysis conducted by the loan officer or inconsistent information provided by the client. If the institution does not record missing values consistently it precludes the use of potentially predictive variables, or confuses the real value of a given characteristic.

Additional reflections on databases. Statistical scoring requires a significant volume of good-quality data. Those institutions that already have adequate databases should start to enter information on loan officer judgment, credit bureau reports, and rejected applications into their information systems. Those MFIs whose information systems are weaker will need to undertake dramatic improvements in order to be able to effectively use credit scoring in the future. Improving the quality of the database is hard work, but the multiple impacts that credit scoring can have on risk assessment and portfolio management make the work worthwhile.

LIMITATIONS OF SCORING IN MICROFINANCE

As mentioned before, the development of scoring models can have a significant impact on microfinance by reducing its still high transaction costs and by improving credit decisions and portfolio management. However, the development of scoring models with strong prediction power for the informal sector is not an easy task, due to the lack of information on client revenues and the marginal coverage of the informal sector by credit bureau networks in most developing countries.

To construct powerful scorecards, MFIs will need to invest more resources and time to improve dramatically the quality of their databases. Where MFIs have stored enough information of good quality to build scoring models, initially they will need to combine it with the subjective knowledge of their loan officers to have positive results. Once the scorecard has been proved and adjusted it could help to streamline the credit approval for renewals.

1. COST OF IMPLEMENTING SCORING

a. **Collecting and entering the data** required to construct a scorecard incurs data accumulation costs. For the least sophisticated institutions, those costs can be significant, considering not only the need for a significant increase in the volume and quality of the data collected, but also the necessary improvements in information systems to capture and store it. Finally, the investment to train loan officers to collect the additional data required is considerable. For some more sophisticated microlenders, data accumulation costs are already sunk; they already enter all applications as they are received. For these lenders, scoring is possible as soon as the database has enough cases to support the scoring model.

b. **The scoring project** itself represents a significant cost, including: the scorecard construction, integration with the information system, adjustment of the information system, training of end users, and follow up. In particular, adjusting the information system to automatically compute and report risk forecasts can be long and difficult and can represent a large share of the projected budget.

c. **The daily use of scoring is time-intensive** for data entry personnel, loan officers and credit managers not only in gathering additional data, but also in analyzing the scoring reports during the credit committee meetings, and training personnel in the use and interpretation of results.

d. **There are costs associated with accepting the results of scoring.** The institution will need to determine how comfortable it is with automatic approval or rejection of loans based on scoring. One way to minimize the costs of automatic rejection is to implement a process for periodic review of sample results of loan scoring versus more subjective approaches, to ensure that the overall loan approval policies are appropriately reflected. Forecasts are not 100% accurate and some rejected loan applicants might have been good clients.

e. The implementation of scoring puts significant emphasis on **the information department**, creating some tension between this group and the credit department staff. Some employees openly oppose scoring's changes, and others ignore policy rules or do not follow the traditional evaluation. Training and follow up are the best ways to manage these process costs.

CREDIT SCORING IMPLEMENTATION PROCESS

1. INITIAL INTRODUCTION AND MODEL CUSTOMIZATION

Most senior managers of MFIs have heard of scoring; attitudes towards the technology range from high expectations to skepticism and resistance. An introduction to scoring is key to bring everyone to the same page. However, discussion with senior managers is vital throughout the process. Although scoring is basically a mathematical formula, its implementation requires important changes in organizational culture. This makes scoring projects larger, longer and more difficult than most managers anticipate.

During the initial introduction it is important to create realistic expectations and to discuss with managers and staff how scoring can help them achieve their mission. The following questions are key in defining the adequate model for an institution:

- According to the staff, what are the most important characteristics that determine risk?
- What is a bad loan for you?
- How many good credit risks would you sacrifice for a bad credit risk?
- How far back can you go before the past is unlike the future?
- What parts of the database would you distrust?
- How easily can the MIS be adjusted to accommodate scoring?

After an exchange of ideas and concepts between the staff and the project leaders (consultant) the statistical work to build the model can start.

2. SCORECARD CONSTRUCTION

To build accurate and strong statistical models, project leaders must be selected who have broad experience in modeling statistical scoring, and who are familiar with the special features of the informal sector that will affect the scoring model. The project team (staff from the institution and project leaders) should discuss and define the attributions of risky clients, which is a very delicate and lender-specific definition. Some lenders consider a risky client one who is more than three days late per installment on average. Other institutions are more flexible in their definition and consider clients to be risky when they are more than 15 days late per installment on average.

Once you have defined your risky client or dependent variable of the scoring model, the analysis of the database can start; this period is key in determining the quality of the database and in defining which variables are available or usable for the model. This is a period of intensive exchange and communication between the consultant and the institution's MIS department to clearly understand the exact definition and interpretation of each variable. Once the database has been analyzed and the data has been cleaned, the statistical modeling phase can start. This process can last from a couple of weeks to several months, depending on the quality of the data and responsiveness of the MIS department.

3. Staff Training

Once the scoring model is constructed, the results are presented and discussed with senior management to review basic concepts and to present concrete, lender-specific results, including the outcome of the historical test and links detected between characteristics and risk.

The results are then presented at the branch level, with the objective of introducing the model to loan officers and credit managers. This introduction focuses more on concrete examples from the historical test and from the constructed scorecard. These meetings are costly, but not doing them would be a mistake. Even after proving to loan officers that scoring works, they may be resistant to its application at first. Front line personnel need some time to absorb and accept the tool.

During this step it also is very important to encourage discussion and to test scoring against loan officers' wisdom and experience. It is crucial to ask questions and encourage discussion:

- Are the links between risk and characteristics consistent with your field experience?
- What are the causes that may explain those links?
- What do you look for when you make a field visit?
- What data do you gather in the field that is untrustworthy in the database?
- What characteristics would you recommend recording for use in future scorecards?
- When do you approve a loan provisionally?
- How can you modify terms and conditions of the loan contract to manage risk?
- How much time per week do you spend in collections?
- How much time per week do you spend in marketing, evaluation, and disbursement?

4. Integration of Scoring into MIS

The next step is to automate the use of scoring by integrating it into the MIS. Many managers prefer to avoid changing anything in the information system, but in order to use scoring at the branch level, automation is the only alternative. There are two broad approaches:

- In the first, the microlender buys previously developed scoring system software from a consultant. This is a quick option, but presents some challenges. The software is expensive, and as a parallel system to the MIS, data may have to be entered twice. Finally, the lack of integration into the MIS poses a considerable threat of not using the scoring system at all.

- In the second approach, the microlender integrates the scorecard and associated reports directly into the existing information system. This approach also poses considerable challenges. First, the institution must be able to modify and adjust its information system. Second, the lender must dedicate a full-time programmer to scoring. Depending on each system, integration could take three to six person months. Third, the technical challenges of integration vary by lender; sometimes unforeseen problems can delay it. Still, integration has important advantages: data is entered only once, scores are produced automatically, and risk forecasts can be integrated directly into the most relevant reports. Weighing both pros and cons, integration is the preferred approach.

Scoring Reports and Applications

1. Definition of a Scoring Policy

A written policy should specify risk thresholds as well as actions for each threshold. For example, the policy should establish the risk level below which cases qualify as excellent credit risks, and the risk level above which cases qualify as unacceptable credit risks. The policy also establishes the risk levels that correspond to normal and borderline credit decisions.

Furthermore, the written scoring policy informs how to reward clients who are excellent credit risks. For borderline cases, it informs how the credit committee should prioritize attempts to mitigate risk, whether by decreasing loan size, decreasing term to maturity, and/or increasing guarantee coverage. Finally, the scoring policy should emphasize that unacceptable credit risks must be rejected.

2. PRE-APPROVAL—SCORING

Scoring Simulator

A credit committee commonly analyzes how modifying borderline cases would affect the risk forecast. The scoring simulator produces sensitivity analyses that can help the credit committee make decisions on loan modifications. For example, Figure 1 shows how predicted risk might change as elements of the loan contract are modified, such as the amount requested, the term to maturity or the guarantee.

Effects of Characteristics Report

This report allows staff to see the reasons behind a risk forecast, which can help staff feel more confident with the scoring technology. For a given application, the report shows the characteristics that most increase risk and those that most decrease risk. See figure 2.

3. THE GLOBAL FOLLOW-UP REPORT

This report tracks the ongoing performance of scoring. It is like a historical test that compares predicted risk with realized risk, but unlike a historical test, it applies to outstanding loans. The Global Follow-Up Report is a central report of scoring; it checks whether scoring works with active loans. Like other scoring reports, it is produced automatically by the system.

Initially, it is hard to interpret scoring. For instance, what does a 30% predicted risk of default mean? At which risk level might a client become a defaulter? During the first month of scoring, the lender should consult the report weekly to check predictive power and to guide adjustments to policy. After that, monitoring could be done on a monthly basis. Figure 3 shows the Global Follow-Up Report based on a regression scorecard. "Risky" is defined as an average of four days of arrears per installment due at the time of the report or a spell of arrears of 30 days.

The left column "forecast risk (%)" defines the range of predicted risk for each row. The lender defines the number of ranges as well as their boundaries. The second column from the left is the share of loans outstanding whose predicted risk falls within a row's range. It shows the distribution of predicted risk in the outstanding portfolio. For example, 0.5% of loans outstanding had a predicted risk of zero to 2%. Likewise, 9.5% had predicted risk in excess of 40%.

The four center columns "Realized risk (%) by days since disbursement" show realized risk for outstanding loans, given a predicted risk and age. The row-by-row comparison of realized risk with predicted risk reveals the scorecard's power. The closer predicted risk is to realized risk, the greater the predictive power.

Figure 3 illustrates a general point: realized risk increases with age after disbursement. Two factors explain this. First, some recent loans have not had an installment come due yet, so they have not had a chance to go bad. Second, arrears increase toward the end of the loan (Vogelgesang, 2001 cited by Schreiner, 2002). Thus, the best test of predictive power could be observed in those loans recently paid-off or in well-aged loans.

The right hand column of the report shows realized risk for recently paid-off loans (the lender determines how many months to review; the example uses 12 months). This is the key column, both because it covers loans of all terms to maturity and because recently paid-off loans have had a full chance to go bad.

The uses of the Global Follow-Up Report are the following:

- **Check predictive power.**
- **Track overrides.** Loans disbursed with predicted risk greater than the unacceptable threshold are, by definition, overrides. Overrides can be abused, so managers must track their outcomes by examining changes through time in realized risk among disbursed "super-bads" or unacceptable risks.
- **Adjust absolute inaccuracies.** Unfortunately, no scorecard has perfect absolute accuracy. The Global Follow-Up Report, however, shows the levels of realized risk that correspond to given levels of predicted risk. Given this information, the user can adjust the level of predicted risk to converge it as much as possible to realized risk.

- **Set or adjust policy thresholds.** By showing the share of loans in each risk range and the level of realized risk that corresponds to a given level of predicted risk, the microlender can set or adjust policy thresholds. This report is especially helpful to determine the ranges of predicted risk above or below which a client becomes an excellent or unacceptable risk.
- **Detect scorecard degradation.** Because the future resembles the recent past more than it resembles the distant past, the predictive power of a scorecard degrades with time. The report shows the evolution of the prediction power of the scorecard over time.

4. Post Disbursement Scoring

Loan Officer Follow-Up Report

The Global Follow-Up Report is central to scoring, but for loan officers and credit managers, it may be too abstract and too broad. Front-line personnel often prefer simpler reports that allow them to compare predicted risk with repayment performance for individual borrowers whom they know personally.

The Loan Officer Follow-Up Report shown in Figure 4 adds measures of predicted risk and repayment performance (realized risk) to the portfolio reports that loan officers and credit managers already receive daily or weekly. In this case, "risky" is defined as clients who have at least one spell of arrears of 30 days during the lifetime of the loan. On the super-bad side, Figure 4 shows the ten highest risk outstanding loans that were disbursed at least 270 days before the date of the report. In this group of outstanding loans, average predicted risk is 61% (bottom-right corner), and average realized risk is 50%.

Figure 4 also shows the ten lowest risk loans. Average predicted risk is less than 1%, and not a single case defaulted. For loan officers and credit managers, seeing reports on their own borrowers goes a long way towards dispelling doubts about whether scoring can accurately identify high risk and low risk clients among those already approved by the credit committee.

This report helps loan officers decide which clients to visit first. For example, clients from the list in Figure 4 would include three high risk, high value loans that have yet to go bad:

- $1,323 outstanding with predicted risk of 80%
- $5,773 outstanding with predicted risk of 62%
- $5,683 outstanding with predicted risk of 72%

In a "courtesy visit," loan officers visit these clients, not in relation to collection activities but rather to discuss any non-threatening topic. By no means should loan officers mention to the clients the real source of the friendly visit. Borrowers in good standing are likely to take offense if they feel suspected of future default. The mere presence of the loan officer is enough to reinforce the importance of timely repayment in the mind of the borrower.

Collection Scoring

Collection scoring predicts the probability that a loan currently one day late will eventually become 15 or 30 days late. In practice, the collection score would be added to the daily report on delinquent loans. Then, based on collection risk and on value-at-risk, loan officers would decide which clients should be visited first and how much pressure should be exerted on them. Cases with high risk and high value at risk would receive immediate, assertive visits. Low risk clients may be contacted by phone one day after they miss a payment.

Managing Renewal: How to Leverage Information

An important impact of scoring in the near future is the possibility it offers to automate and streamline the loan renewal process. The most profitable clients are those with longer life cycles with the lender and an excellent repayment behavior.

Profitable clients enable the institution to make larger profit margins due to small additional investments in updating the information. Some lenders have created "special loan officers" who are able to manage 1,000 to 2,000 good clients, due to the low maintenance costs. Loan officers only visit clients to update the information every two years. Scoring could identify those clients with higher risk and prioritize their visits to update the economic information.

Customer Loyalty (Desertion Scoring)

Desertion scoring predicts the probability that a borrower will apply for another loan once the current one is paid off. Microlenders seek to prevent desertion because profitability usually increases with each repeat loan (Churchill and Halpern, 2001; Rosenberg, 2001 cited by Schreiner). If the lender is able to determine which clients were at risk of dropping out, then loan officers could encourage clients to take out subsequent loans, perhaps by offering reduced interest rates or other type of incentives.

Visit Scoring

Visit scoring predicts the probability of rejection after the field visit. Such rejected cases cost loan officers time without producing any revenue. In some cases, post-field visit rejections represent 40% of the cases visited. Visit scoring cuts down on the number of fruitless visits by forecasting rejection risk based on characteristics captured in the first contact application. Of course, visit scoring can be used only to reject without a visit, not to accept without a visit.

Portfolio Risk Management

Scoring could be a powerful tool to assess portfolio risk levels and trends among different economic activities that are financed. Managers can set different risk tolerance levels according to their profitability or impact targets. Scoring can help them monitor risk level changes periodically. Also, if the lender is interested in attracting potential investors or creditors, scoring can help assess the average risk of the portfolio, and even map risk level by type of activity, region or amount financed. Potential stakeholders can have a very detailed picture of the potential risk of their investments.

CONCLUSIONS

Scoring measures the risk that the self-employed poor will not pay as promised. Scoring also identifies the links between repayment and the characteristics of the borrowers, loans and loan officers and makes these explicit. Most importantly, scoring provides the possibility of making decisions based on quantified risks and explicit trade offs. This may induce a shift in organizational culture as managers start to seek greater knowledge and precision about alternatives and consequences in all of their decisions. Although simple data analysis can inform decisions, most microlenders have yet to invest in building accurate and comprehensive databases.

On average, scoring in microfinance in developing countries predicts with a significant level of accuracy. The number and range of mistakes, however, are much larger than for scoring in high income countries. Much of the risk associated with lending to self-employed workers is unrelated to quantifiable characteristics. Thus scoring complements, but does not replace, loan officers' evaluations. Scoring is a third voice in the credit committee, a support for the judgment of the loan officer and credit manager.

Even if scoring works perfectly, acceptance requires repeated training for stakeholders at all levels and permanent follow up with constant demonstrations of predictive power for outstanding loans. The definition of clear scoring policies and their enforcement are key to the adequate implementation of scoring.

FIGURE 1. EXAMPLE "SCORING SIMULATOR" OF RISK FORECAST AFTER MODIFICATIONS TO LOAN TERM				
Client: Juan Perez		Branch: Central		App no.: 12345
Loan Officer: Isabel Sanchez		Committee: 01/03/02		App. Date: 1/1/02
	Amount Disbursed (US$)	Term to Maturity	Guarantee (%)	Predicted Risk (%)
Requested Term	1,000	10	100	40
Sensitivity Tests:				
Amount disbursed	900	10	100	38
	800			33
	700			29
Term to Maturity	1,000	9	100	37
		8		32
		7		27
Guarantee (% amt.)	1,000	10	125	39
			150	37
			200	36

FIGURE 2: EXAMPLE "EFFECTS OF CHARACTERISTICS REPORT"			
Client: Juan Perez	**Case: A 12345**		**Risk: 30 days of arrears in a row**
Loan Officer: Isabel Sanchez	**App. date: 6/2/02**		**History: 1/1/95 to 5/1/02**
Characteristics	**Actual Value**	**Historical Average**	**Effect (% pts.)**
1. Days of arrears/installments, last paid-off loan	8.7	1.7	(+) 5.8
2. No. late installments, last paid-off loan	6.0	4.0	(+) 4.2
3. Exp. loan officer (no. disbursed)	77.0	535.0	(+) 3.7
4. Type of business activity	Carpentry	N/A	(+) 1.5
5. Telephone in the residency	No	Yes	(+) 1.1
6. Term to maturity, last paid-off (month)	8.0	10.5	(+0.6)
7. Rotation of capital (%)	Missing	326.0	(+) 0.3
8. Repayment burden (%)	20.0	18.0	(+) 0.1
36. Guarantee coverage (%)	350.0	300.0	(-) 0.4
37. Client gender	Woman	Woman	(-) 0.7
38. Total no. of employees		0.3	(-) 1.9
39. Exp. client (no. month)	36.0	14.0	(-) 2.3
40. Client age	55.0	43.0	(-) 4.4
RISK FORECAST	23.2	9.3	(+) 13.9

Notes:

Actual value:	value of the characteristics of a particular client
Historical Average:	value of the characteristics of an average client
Effects % pts:	difference between the value of the characteristics of a particular client and the value of the characteristics of an average client. The variance of each characteristic from its corresponding average represents the current effect of each characteristic on total risk

FIGURE 3: EXAMPLE "GLOBAL FOLLOW-UP REPORT"						
Risk: 4 Days/Installment or 30/Row		Quantity at-Risk: Number of Loans				
Date Tested: 6/2/02		Date Score Card Constructed: 7/31/01				
		Realized Risk (%) by Days Since Disbursement				Realized Risk (%) For Loans Paid Off in Last 12 Months
Forecast Risk (%)	% of Total Portfolio	0-90	91-180	181-270	271 +	
0-2	0.5	1.40	2.00	0.00	4.00	3.2
2-4	5.1	2.80	2.80	2.10	3.50	3.1
4-6	7.8	3.00	4.00	4.00	5.10	4.7
6-8	8.1	3.90	4.80	5.50	8.10	7.8
8-10	7.7	5.30	6.70	6.40	11.50	10.6
10-15	17	5.50	8.10	11.60	18.10	16.3
15-20	14.5	6.80	12.10	17.90	27.60	24.7
20-25	11.4	9.00	16.90	23.80	33.10	27.2
25-30	8.4	11.40	19.40	30.40	37.80	36.3
30-40	10	14.60	25.00	37.30	45.80	43.1
40-50	5.1	18.40	30.40	50.90	53.60	52.6
50-60	2.7	23.00	42.30	57.20	60.40	60.1
60-70	1.2	32.40	42.60	65.20	70.50	70.3
70-100	0.5	34.30	62.90	65.50	77.90	75.4

FIGURE 4: EXAMPLE "LOAN OFFICER FOLLOW-UP REPORT" HIGHEST RISK AND LOWEST RISK											
Report date: 7/31/2001			Branch = All		Risk = 1 spell >= 30 days						
Loan No.	Client	Days Out	$ Outstanding	Monthly Payment	Next Due	Current Arrears	No. Spells	Realized Risk Arrears/Install	Longest Spell	Bad	Predicted Risk
123	Javela Maria	308	2,106	83	3-Aug	23	2	42.5	77	Bad	90
94	Posada Maria	334	1,860	71	29-Aug	0	3	21.1	36	Bad	81
230	Arboleda Nivelly	336	1,323	132	29-Aug	2	3	14.8	25	Good	80
95	Beltran Josefina	304	1,032	48	29-Aug	0	3	14.8	42	Bad	80
96	Nunez Dolly	337	5,683	316	2-Aug	0	1	22.7	28	Good	72
97	Cruz Leonor	304	377	22	29-Aug	0	3	45.5	101	Bad	71
98	Rivera Antonia	304	603	39	29-Aug	23	2	22.2	39	Bad	68
122	Marin Graciela	337	5,773	283	29-Aug	0	4	14.5	25	Good	62
123	Munoz Marco	304	2,003	111	29-Aug	0	3	25.7	67	Bad	60
90	Silva Osy	304	388	29	29-Aug	86	2	36	86	Bad	59
201	Valencia Lucer	292	59	60	18-Aug	0	0	0	0	Good	0.5
202	Betancurt Jose	305	73	26	1-Aug	0	1	0	0	Good	0.5
603	Valencia Juan	279	35	36	5-Aug	0	0	0	0	Good	0.5
604	Fernandez Zorrila	281	289	38	7-Aug	0	0	0	0	Good	0.5
505	Sanchez Hernan	290	102	36	16-Aug	0	0	0.1	1	Good	0.5
506	Escobar Patricia	316	107	32	11-Aug	0	1	7	13	Good	0.5
507	Echandia Henry	322	102	36	17-Aug	0	0	0	0	Good	0.6
508	Jaramillo Emma	285	289	103	11-Aug	0	1	0.1	1	Good	0.6
509	Guevara Cesar	295	87	31	20-Aug	0	0	0	0	Good	0.6
510	Paz Maria	336	768	167	1-Aug	0	1	0.8	5	Good	0.6

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