

Credit Scoring for Microfinance

Can It Work?

by Mark Schreiner

ABSTRACT: In rich countries, lenders often rely on credit scoring—formulae to predict risk based on the performance of past loans with characteristics similar to current loans—to inform decisions. Can credit scoring do the same for microfinance lenders in poor countries? This paper argues that scoring does have a place in microfinance. Although scoring is less powerful in poor countries than in rich countries, and although scoring will not replace the personal knowledge of character of loan officers or of loan groups, scoring can improve estimates of risk. Thus, scoring complements—but does not replace—current microfinance technologies. Furthermore, the derivation of the scoring formula reveals how the characteristics of borrowers, loans, and lenders affect risk, and this knowledge is useful whether a lender uses predictions from scoring to inform daily decisions. In the next decade, many of the biggest microfinance lenders will likely make credit-scoring models one of their most important decision tools.

Introduction

Credit scoring uses quantitative measures of the performance and characteristics of past loans to predict the future performance of loans with similar characteristics. For lenders in wealthy countries during the past decade, scoring has been one of the most important sources of increased efficiency. Such lenders, however, score potential borrowers on the basis of comprehensive credit histories from credit bureaus, as well as on the experience and salary of the borrower in formal wage employment. Most

microfinance lenders, however, do not have access to credit bureaus, and most of their borrowers are poor and self-employed. The two chief innovations of microfinance—loans to groups whose members use social capital to screen out bad risks, and loans to individuals whose loan officers know them well enough to screen out bad risks—rely fundamentally on qualitative information held in human memory. Scoring, in contrast, relies fundamentally on quantitative information stored in lenders' computers. Can microfinance lenders use scoring to cut the costs of arrears and loan evaluations so as to improve efficiency, and thus both outreach and profitability?

Experiments in Bolivia and Colombia (Schreiner, 2000, 1999a, 1999b) suggest that scoring for microfinance can indeed improve the judgment of risk and thus cut costs. For example, scoring may save a Colombian microfinance lender as much as \$75,000 per year (Schreiner, 2000). In present value terms, this approaches \$1 million.

Scoring may be the next important technological innovation in microfinance, but it will not replace loan groups or loan officers. In Bolivia and Colombia scoring will never be as effective as in wealthy countries because much of the risk of microloans is unrelated to characteristics that can be quantified inexpensively. Still, scoring is useful in microfinance because some risk is related to characteristics that are inexpensive to quantify, and current microfinance technologies do not take full advantage of this. This paper describes how scoring works, what its

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capabilities are, and how microfinance lenders should prepare themselves to implement it. Other basic introductions to scoring include Mays (1998), Hand and Henley (1997), Mester (1997), Viganò (1993), and Lewis (1990).

How Scoring Models Work

Scoring assumes that the performance of future loans with a given set of characteristics will be like the performance of past loans with similar characteristics. If the future is not like the past—as is often the case for microfinance lenders who grow, develop new products and niches, confront competition, or work in fluctuating markets—scoring will not work well.

A *credit-scoring* model is a formula that puts weights on different characteristics of a borrower, lender, and loan. The formula produces an estimate of the probability or risk that an outcome will occur. For example, suppose a lender wants to estimate the likelihood (risk) that a given loan to a given borrower will result in at least one incident of arrears of seven or more days. A simple scoring model might state that the base risk for very small loans to manufacturers is 0.12 (12 percent), that traders are 2 percentage points (0.02) less risky, and that each \$100 disbursed increases risk by half a percentage point (0.005). Thus, a trader with a \$500 loan would have a predicted risk of 12.5 percent ($0.12 - 0.02 + 5 \times 0.005$), and a manufacturer with a \$1,000 loan would have a predicted risk of 17 percent ($0.12 + 0.00 + 10 \times 0.005$). The weights in the formula are derived from statistics, but the math is elementary; the difficulties arise in collecting data on the performance and characteristics of past loans, grafting scoring into the current loan-evaluation process, and adjusting the organization to accept a technique so fundamentally different from what has previously been successful.

Databases for Scoring

Microfinance lenders who wish to someday use credit scoring should begin collecting appropriate data now. Without a database on the performance and characteristics of many past loans, scoring is impossible; lenders with small portfolios may never benefit from scoring. The database must be computerized, and ideally it would include both approved and rejected applicants, although most lenders only keep approved applicants' records. The database should also include a full range of borrower, lender, and loan characteristics, as well as data on the timing and length of each arrears spell. Such characteristics are simple and inexpensive to collect, and most microfinance lenders compile them when a loan officer visits a potential borrower.

All microfinance lenders who want to use scoring—even those who already have large, comprehensive databases—should start to quantify and record the subjective assessments of loan officers. In the field, loan officers would still be free to “sniff” for hints of risk as they see fit, but in the office, they should convert their subjective judgments into quantitative forms amenable to scoring. For example, they may rate potential borrowers as very below average, below average, average, above average, or very above average on such qualities as reputation in the community, entrepreneurship, experience with debt, and informal support networks.

Perhaps the greatest lesson of scoring is that the rigorous analysis of a database containing past microfinance loans offers vast power to improve managerial decisions. A large, accurate, and comprehensive database on past loan performance is an asset that many microfinance lenders have failed to develop or use to its fullest.

What Type of Risk to Predict

Once data are in hand, microfinance lenders must choose what types of risk to predict. Scoring is most useful for risks that are costly for the lender and that the lender has some power to control. For example, one-day spells of arrears may be frequent but not very costly, whereas fifteen-day spells may be infrequent but very costly. Scoring is better used to predict fifteen-day spells than one-day spells. Likewise, scoring can be used to predict default due to borrower's death, but lenders have no control over this risk, even if they can predict it.

Given these criteria, six basic types of scoring models are relevant for microfinance. The first model predicts the likelihood that a loan currently outstanding or currently approved for disbursement under the standard loan-evaluation process will have at least one spell of arrears of at least x days (Schreiner, 2000 and 1999b). This information can be used to guide risk-based pricing or to mark potential loans for extra review and outstanding loans for a preventive visit from a loan officer before they fall into arrears. The second type of model predicts the likelihood that a loan x days in arrears will eventually reach y days of arrears. This information can be used to prioritize visits by loan officers to delinquent borrowers. The third type of model predicts the likelihood that a borrower with an outstanding loan in good standing will choose not seek a new loan once the current debt is repaid (Schreiner, 1999a). This information can be used to offer incentives to good borrowers who are likely to drop out. The fourth type of model predicts the expected term to maturity of the next loan of a current borrower. Likewise, the fifth type of model predicts the expected disbursement size of the next loan. Sixth and finally, the ultimate scoring model combines information from the first five models; knowledge of the expected revenue of a loan with a given term to maturity and disbursement; and knowledge of the expected

costs of dropouts, loan losses, and monitoring borrowers in arrears. This ultimate model—currently used by credit card lenders in wealthy nations—estimates the financial value of the lender-client relationship. Rather than gauging the client's risk, it measures her profitability. Estimating profitability does not imply that lenders must reject all unprofitable clients; it merely helps them to recognize the trade-offs between profits and depth of outreach (Schreiner, 1999c). Most microfinance lenders tend to start with one simple model, and if they find that it works well, they add the other simple models one at a time.

Scoring in a Microfinance Organization

The greatest difficulties in a credit-scoring project are not technical but organizational. Given a database, consultants can straightforwardly derive a scoring formula. The difficult part is the implementation of the formula in an existing organization with an existing lending technology. Managers and board members must understand the strengths and weaknesses of scoring so they can commit to support its adoption and integration within the organization. Otherwise, a scoring model may sit unused; an unused model serves no purpose, and a misused model is worse than no model at all. One way to encourage managers to support a scoring project is to ask them to choose a type of risk to model, suggest which characteristics to include in the formula, and then design the implementation. Loan officers and credit managers in the branches may feel threatened by scoring; they have devoted time and effort to learning to judge risk and may be suspicious of a computer program—written by someone who has never met one of their clients—that claims to improve on their judgments. The employees who run the management-information system must also be brought onboard. At first, they may view scoring as nothing more than extra work, but they will soon recognize it as a fundamental transfer of organizational power toward their department.

Ease of Use

One key to the acceptance of scoring in an organization is ease of use. This requires that scoring systems be integrated into the existing management-information system and that they require little data entry beyond standard processes. Such integration also allows the estimates of risk to be included in standard reports. In Colombia, for example, the management-information system generates a report with the estimated risk of “costly arrears,” along with other key information about potential loans to be reviewed in the daily meeting of the credit committee in each branch. Loan officers also receive a list of their currently outstanding borrowers in order of estimated risk, thereby prioritizing preventive visits. In short, a good scoring system allows a lender to continue with business as usual, but with the addition of quantitative estimates of risk.

Out-of-Sample Tests

The acceptance of scoring within an organization also requires a proven track record. One of the greatest strengths of scoring is that it can establish a track record even before being put to use. For example, Schreiner (2000) derived a scoring formula from data on loans disbursed in 1993–1998. This formula was then used to estimate the risk of arrears for loans disbursed in 1999. Because the performance of these loans was already known, the comparison of predicted and observed risk showed how the model would have performed had it been used in 1999. Such inexpensive out-of-sample tests are perhaps the best way to convince skeptical managers that scoring works for microfinance.

Tracking Performance in Use

Once in use, scoring continues to build a track record. Lenders with scoring models must track both predicted risk and actual performance, even if they decide to ignore the risk estimate from the model. Through

time, careful records will reveal how well the model works. For example, if scoring works well, 20 percent of loans with a 20 percent estimated risk of “costly arrears” should turn out to have such arrears. Likewise, lenders must track overrides—cases in which credit policy dictates a certain action for loans above (or below) a risk threshold, but in which loan officers or credit managers break with policy because they know something the scoring model does not. They often do know more, and it is important to track the outcomes of overrides to determine how much they improve on the scoring model. Because scoring works only if the past is like the present, and because the recent past is more like the present than the distant past, the performance of scoring models degrades with time; careful tracking helps to signal when a formula needs to be rebuilt.

How Characteristics Affect Risk

Beyond estimates of risk, the process of developing a scoring formula reveals a lot about how the characteristics of the borrower, loan, and lender affect risk.

Characteristics of the Borrower

In Bolivia, the derivation of the formula shows that past arrears help to predict future arrears: compared with borrowers with no arrears in the previous loan, borrowers with arrears of more than 15 days in the previous loan were 2.8 percentage points more likely to have a spell of at least 15 days in the current loan (Schreiner, 1999b). Manufacturers were about 4 percentage points riskier than traders, and first-time borrowers were about 1.2 percentage points riskier than second-time borrowers. This knowledge helps to target marketing campaigns and screen applicants.

Characteristics of the Loan

The derivation of the formula also reveals how the terms of the loan contract affect risk. In Colombia, the risk of loans with monthly installments increased by about 3 percentage points for each additional installment (Schreiner, 2000). Likewise, given the number of installments, a loan repaid monthly was about 0.6 percentage points riskier than a loan repaid weekly. Colombian lenders used these results to adjust loan contracts until expected risk was acceptable.

Characteristics of the Lender

Finally, the derivation of the scoring formula illustrates how the lender affects risk. In Bolivia, the borrowers of the loan officer with the least risk of dropouts were about 25 percentage points less likely to drop out than were the borrowers of the loan officer with the greatest risk (Table 1; Schreiner, 1999a). This knowledge could guide the allocation of performance bonuses or help to target training. In Colombia, scoring showed that most learning by loan officers occurs directly after they start work (Figure 1; Schreiner, 2000). Compared with loans from a new loan officer, loans from a loan officer who has had experience with 50 disbursements are about 7 percentage points less likely to have “costly arrears” than loans from an inexperienced loan officer. An increase of experience from 50 to 1,100 disbursements decreases risk only by about 2 additional percentage points.

Selecting a Scoring Model

Scoring is difficult for any lender, and scoring for microfinance is even more exacting. As discussed, the main difficulties are the organizational adjustments required to integrate scoring into the lending process. Amassing an adequate database is a second challenge, and a third difficulty is that one size does not fit all. Because of differences in lending

technology, clientele, competition, and general economic environment, a scoring model developed from the database of one lender will be much less powerful if applied to a second lender.

To my knowledge, scoring models have been built for microfinance lenders in Bolivia, Burkina Faso, Colombia, Chile, México, Panamá,

Table 1: How the Specific Loan Officer Affects the Risk of Dropouts in Bolivia

Loan officer	Effect on risk
1	-0.048
2	-0.038
3	-0.037
4	-0.037
5	-0.033
6	-0.025
7	-0.024
8	-0.024
9	-0.023
10	-0.020
...	...
30	0.005
31	0.005
32	0.007
33	0.007
34	0.008
35	0.009
36	0.009
37	0.021
38	0.021

Source: Schreiner (1999a)

**Figure 1: How the Experience of a Loan Officer
Affects the Risk of “Costly Arrears” in Colombia**

Perú, and Thailand. Only the models in Schreiner (1999a, 1999b, and 2000) use statistics to derive the scoring formula; the rest use simple heuristics or rules of thumb. Such nonstatistical models may be better than no model at all, especially if a lender lacks a database capable of supporting a statistical model. Statistical models, however, probably have greater predictive power. Furthermore, statistical models *derive* the relationships between specific characteristics and risk; rule-of-thumb models *assume* these relationships. Regardless of the technique used to derive the formula, the power of any scoring model should be demonstrated in an out-of-sample test before implementation.

Conclusion

The essence of finance is the prediction of the risk—whether borrowers will keep their promises. Risk estimates are based on information; and in microfinance, this information is usually qualitative and informal—it resides with group members or with loan officers. Credit scoring takes a different tack. It predicts risk based on quantitative information that resides in the management-information system of the lender.

Credit scoring for microfinance can work. It is not as powerful as scoring for credit card or mortgage lenders in wealthy countries, and it will not replace the judgments of loan officers or loan groups based on informal, qualitative knowledge, but scoring does have some power to predict risk (and thus to cut costs) even after the group or loan officer makes its best judgment. Thus, scoring complements—but does not replace—current microfinance technologies. Furthermore, scoring not only helps to predict risk, but also reveals how characteristics of the borrower, the loan, and the lender affect risk. This knowledge is useful whether a microfinance lender uses risk predictions from scoring to inform daily decisions.

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