Credit Scoring for Microfinance: Can It Work?

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November 2000

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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 or not 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.

Acknowledgments

A later version of this paper appears in *Journal of Microfinance*, (2000) Vol. 2, No. 2, pp. 105-118. I am grateful for support from the Division of Asset Building and Community Development of the Ford Foundation. I also thank the microfinance lenders in Bolivia and Colombia for the use of their data bases and their willingness to pioneer credit scoring for microfinance. Hans Dellien was instrumental in the work in Colombia.

Author biography

Mark Schreiner is Research Director in the Center for Social Development at Washington University in St. Louis. He studies ways to help the poor to build assets through access to loans and saving services. In the United States, his research interests are development-based welfare policy, Individual Development Accounts, and microenterprise. In the third world, his research interest is microfinance. He has measured the social cost-effectiveness of Grameen Bank in Bangladesh and BancoSol in Bolivia, and he made the first statistical credit-scoring models for microfinance.

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1. 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 rich countries in the past decade, scoring has been one of the most important sources of increased efficiency. Lenders in rich countries, however, score potential borrowers based on comprehensive credit histories from credit bureaux and on the experience and salary of the borrower in formal wage employment. Most microfinance lenders, however, do not have access to credit bureaux, and most of their borrowers are poor and self-employed. The two chief innovations of microfinance—loans to groups whose members use their social capital to screen out bad risks and loans to individuals whose loan officers get to know them well enough to screen out bad risks—rely fundamentally on qualitative information kept in the heads of people. Scoring, in contrast, relies fundamentally on quantitative information kept in the computers of a lender. Can microfinance lenders use scoring to cut the costs of arrears and of 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 judgement of risk and thus cut costs. For example, scoring may save a Colombian microfinance lender about $75,000 per year (Schreiner, 2000). In present value terms, this approaches $1 million.

Scoring is probably the next important technological innovation in microfinance, but scoring will not replace loan groups or loan officers, and it will never be as effective as it is in rich countries because much of the risk of microloans is unrelated to characteristics that can be quantified inexpensively. Still, scoring can still be useful in microfinance because some risk is related to characteristics that are inexpensive to quantify, and current microfinance technologies do not seem to take advantage of this as much as they could. This paper describes how scoring works, what it can and cannot do, and how microfinance lenders should prepare themselves to implement it. Other good, general introductions to scoring are Mays (1998), Hand and Henley (1997), Mester (1997), Viganò (1993), and Lewis (1990).

2. 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 often the case for microfinance lenders who grow, develop new products and niches, confront competition, or work in markets in flux—scoring will not work well.

A *credit-scoring* model is a formula that puts weights on different characteristics of a borrower, a lender, and a loan. The formula produces an estimate of the probability or risk that an outcome will occur. For example, suppose a lender might want to estimate the likelihood (risk) that a given loan to a given borrower will have at least one spell 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 two 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 ($0.12 - 0.02 + 5 \cdot 0.005$), and a manufacturer with a $1,000 loan would have a predicted risk of 18 percent ($0.12 + 0.00 + 10 \cdot 0.005$). The weights in the formula are derived with statistics, but, the math is the easy part; the difficult part is to collect data on the performance and characteristics of past loans, to graft scoring into the current loan-evaluation process, and to adjust the organization to accept a technique so fundamentally different from what has been successful so far.

3. Data bases for scoring

Microfinance lenders who want to use credit scoring in the future should start to collect appropriate data now. Without a data base on the performance and characteristics of many past loans, scoring is impossible; lenders with small portfolios may never be able to use scoring. The data base must be computerized, and it ideally would include both approved and rejected applicants, although most lenders will have kept records only on approved applicants. The data base should also include a full range of characteristics of the borrower, the lender, and the loan, as well as data on the timing and length of each spell of arrears in each loan. These characteristics are all simple and inexpensive to collect, and most microfinance lenders already collect them when the loan officer visits a potential borrower.

Furthermore, all microfinance lenders who want to use scoring—even those who already have large, comprehensive data bases—should start to quantify and record the subjective assessments of loan officers. In the field, loan officers are still free to use their sixth sense and to sniff for hints of risk as they see fit, but back at the office, they should convert their subjective judgements into quantitative forms amenable to scoring. For example, they could 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 data base of past microfinance loans may have vast power to improve management decisions. A large, accurate, comprehensive data base on past loans and their performance is an asset that many microfinance lenders have so far failed to develop or use to the fullest.

4. What type of risk to predict

Once data are in hand, microfinance lenders must choose what type 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 probably better used to predict fifteen-day spells than one-day spells. Likewise, scoring could be used to predict default due to the death of the borrower, but lenders have little 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 or outstanding loans for a preventive visit from a loan officer even before they fall into arrears. The second type of model predicts the likelihood that a loan x days in arrears now 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 to get a new loan once the current one 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 size of disbursement of the next loan. Sixth and finally, the ultimate scoring model combines information from the first five models with knowledge of the expected revenue of a loan with a given term to maturity and disbursement and with knowledge of the expected costs of drop-outs, loan losses, and monitoring borrowers in arrears. This ultimate model—currently used by credit-card lenders in rich countries—estimates the financial present value of the relationship with the client. It gauges not the client's risk but rather her profitability. Of course, estimating profitability does not imply that lenders must reject all unprofitable clients; it merely helps them to know better the trade-offs between profits and depth of outreach (Schreiner, 1999c). Most microfinance lenders will most likely start with one of the simple models and, if they find that the first one works well, add the other simple models one at a time.

5. Scoring in a microfinance organization

The most difficult issues in a credit-scoring project are not technical but organizational. Given a data base, 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 that they can commit to support its adoption and integration in the organization. Otherwise, a scoring model might sit unused; an unused model serves no purpose, and a misused model might be worse than no model at all. One way to help managers buy into a scoring project is to ask them to choose what type of risk to model, to suggest what characteristics to include in the formula, and to design the implementation. More importantly, loan officers and credit managers in the branches may feel threatened by scoring; after all, they spent a lot of time and effort to learn to judge risk, and they have a right to be suspicious of a computer program—written by someone who has never met one of their clients—that claims to improve on their judgements. The employees who run the management-information system must also be brought on-board. At first, they may see scoring as nothing more than extra work, but they will soon recognize it as a fundamental transfer of organizational power toward their department.

5.1 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 that already done as part of standard processes. Such integration also allows the estimates of risk to be included in standard reports. In the example of Colombia, the management-information system generates a report with the estimated risk of "costly arrears" along with other key information about the 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, to help to prioritize 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.

5.2 Out-of-sample tests

The acceptance of scoring in 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 can work for microfinance. Whatever the theoretical or statistical weaknesses of the model and whatever the problems with the data base, nothing trumps an out-of-sample test.

5.3 Tracking performance in use

Once in use, scoring also builds a track record. Lenders with scoring models must track both predicted risk and actual performance, even if, at first, 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 where credit policy dictates a certain action for loans above (or below) a risk threshold but where loan officers or credit managers decide to break with policy because they believe they know something that the scoring model does not. Of course, they often do know more, and it is important to track the outcomes of overrides to check 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.

6. 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, the loan, and the lender affect risk.

6.1 Characteristics of the borrower

In Bolivia, the derivation of the formula showed 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 could help to target marketing campaigns or to screen applicants.

6.2 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 increases 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. The Colombian lenders use these results to adjust loan contracts until expected risk is acceptable.

6.3 Characteristics of the lender

Finally, the derivation of the scoring formula shows how the lender affects risk. In Bolivia, borrowers of the loan officer with the least risk of drop-outs were about 25 percentage points less likely to drop out than were 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 very soon after they start work (Figure 1; Schreiner, 2000). Compared with loans from a new loan officer, loans from a loan officer with 50 disbursements of experience are about 7 percentage points less likely to have "costly arrears". An increase of experience from 50 to 1,100 disbursements decreases risk only by about 2 additional percentage points.

7. Selecting a scoring model

For any lender, scoring is difficult, and scoring for microfinance is even more difficult. As discussed, the main difficulties are the organizational adjustments required to integrate scoring into the lending process. A second important difficulty is amassing an adequate data base. A third difficulty is that one size does not fit all; a scoring model developed from the data base of one lender will be much less powerful if applied to a second lender because of differences in the lending technology, the clientele, the competition, and the general economic environment.

To my knowledge, scoring models have been built for microfinance lenders in Bolivia, Burkina Faso, Colombia, Chile, México, Panamá, 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 non-statistical models may be better than no model at all, especially if a lender lacks a data base that can support a statistical model. All else constant, however, statistical models 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.

8. Conclusion

The essence of finance is the prediction of the risk of whether borrowers will keep their promises. Risk estimates are based on information, and in microfinance, this information is usually qualitative and informal and 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. Up to now, microfinance lenders have depended almost exclusively on informal, qualitative information. Can microfinance also benefit from scoring and its use of formal, quantitative information?

This paper has argued that credit scoring for microfinance can work. It is not as powerful as scoring for credit-card or mortgage lenders in rich countries, and it will not replace the judgements 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 judgement. Thus, scoring complements—but does not replace—current microfinance technologies. Furthermore, scoring not only helps to predict risk, but the process of making the scoring formula also reveals how characteristics of the borrower, the loan, and the lender affect risk. This knowledge is useful whether or not a microfinance lender uses risk predictions from scoring to inform daily decisions.

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Table 1: How the specific loan officer affects the risk of drop-outs 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 experience in terms of the number of disbursements by a loan officer affects the risk of "costly arrears" in Colombia