Scoring Drop-Out at a Microlender in Bolivia

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Abstract

This paper presents a scoring model that predicts the risk of drop-out for borrowers at a microfinance lender in Bolivia. Drop-out risk was greater for women, manufacturers, newer borrowers, and those with more arrears. Out-of-sample tests suggest that scoring may help microfinance lenders to detect segments of their clientele (and even specific current clients) who are at-risk of drop-out.

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Le risque de désertion d'emprunteurs d'un prêteur de microcrédit en Bolivie

Ce document décrit un modèle statistique de la qualification du risque que les emprunteurs ne renouvellent pas leurs prêts d'un prêteur de microcrédit en Bolivie. Le risque de désertion est plus grand pour les plus nouveaux emprunteurs, les femmes, les fabricants, et ceux-là avec une durée grande de l'arriéré dans le passé. Le risque dépend aussi de la quantité déboursée, de l'analyste de crédit, de l’agence, et du temps qui a passé depuis le premier prêt. Le modèle statistique qui utilise une information dérivée de la connaissance de caractéristiques quantitatives ne peut pas remplacer les analystes de crédit et sa connaissance du caractère qualitatif de l'emprunteur, mais le modèle a encore pouvoir de prévision dans une certaine mesure. On montre que le modèle peut aider au prêteur de microcrédit à savoir quels emprunteurs ont le plus grand risque de désertion.

El riesgo de deserción de prestatarios de un prestamista de microcrédito en Bolivia

Este documento describe un modelo estadístico de la calificación del riesgo de que los prestatarios no renueven sus préstamos de un prestamista de microcrédito en Bolivia. El riesgo de deserción es mayor para mujeres y manufactureros y para prestatarios con menos créditos o mayor número o duración de atrasos en el pasado. El riesgo también depende del monto desembolsado, del analista de crédito, de la sucursal, y del tiempo que ha transcurrido desde el primer préstamo. El modelo estadístico que usa información derivada del conocimiento de características cuantitativas no puede reemplazar los analistas de crédito y su conocimiento del carácter cualitativo del prestatario, pero el modelo todavía tiene poder de predicción en alguna medida. Se muestra que el modelo puede ayudar al prestamista de microcrédito a saber cuáles prestatarios tienen el mayor riesgo de deserción.

Scoring Drop-Out at a Microlender in Bolivia

1. Introduction

Drop-out (attrition) in microfinance occurs when a good client repays his or her current loan but does not get a new one. For clients, drop-out may be desired (they no longer want loans) or undesired (they are dissatisfied with the lender).

Microfinance lenders seek to manage drop-out, especially in places like Bangladesh and Bolivia where markets are saturated (Rhyne, 2001; Evans *et al.*, 1999; Karim and Osada, 1998). For lenders, drop-out is undesired because it cuts into market share. Drop-out also weakens profitability because lenders lose money on the first few small, short loans that they make to a given borrower until he or she demonstrates creditworthiness (Churchill and Halpern, 2001; Brand and Gerschick, 2000).

Can scoring help microlenders manage drop-out? This paper finds that it can help in two ways. First, scoring highlights at-risk at-risk segments of the clientele. The lender can then investigate why these broad classes of peopleis segment tends to drop-out and perhaps adjust products and policy. Second, scoring identifies specific at-risk borrowers even before they drop- out. The lender might then visit them and encourage them to repeatstay on as clientsloan for the next round.

At the Bolivian microlender studied here, the risk of drop-out was greater for women, manufacturers, newer borrowers, and those with more arrears. Risk also depended on the branch and loan officer. In out-of-sample tests, scoring predicted individual drop-outs wellmuch better than a naïve model.

This briefis paper proceeds as follows. Section 2 sets the stage with descriptions of microfinance in Bolivia, the data, and the scoring model. Section 3 reports results, and Section 4 tests out-of-sample prediction. Section 5 concludes.

2. ScoringA model of drop-out

This section describes microfinance in Bolivia, the data, and the model.

2.1 Microfinance in Bolivia

Bolivia isBolivia is the cradle of microfinance in Latin America and (Hulme and Mosley, 1996). Microfinance has a very high rate of penetration despite the sparse population (—six people per km^2),— deep poverty, and rugged topotopography. Most Latin American countries have, at most, one microlender with more than 10,000 active borrowers; Bolivia has a dozen this big. Several of these large mmicrolenders have converted from unregulated not-for-profits into regulated for-profits. The lenders work in both rural and urban areas and with both individuals and groups. Most borrowers are near the poverty line but are not among the very poorest (Navajas *et al.*, 2000).

The success of microfinance in Bolivia attracted Chilean consumer-finance companies to enter the market in 1995-6 (Navajas et al., 1999; Rhyne, 1999; Poyo and Young, 1999). AThe battle for market share ensued and has continued through 2001. C. Casualties include arrears (more than tripled since that havemore than tripled their 1995) and sharp increases in drop-outs (about doubled). In this context, lenders have sought waysseek to staunch the flow of clients lost to drop-out with careful attention to who dropped out and why.

2.2 Drop-out at one microlender

This study examines drop-out at one Bolivian microlender.[1] From 1988 through 1996, its *drop-out rate* was 18.3 percent, defined as the number of good borrowers who repaid their loans but did not get new loans (6,947) divided by the number of loans

[1] The anonymous lender makes individual loans in urban areas. In 1996, it disbursed 23,000 loans (average $635). In 1999, it became a regulated, for-profit intermediary.

repaid (37,982).[2] In the first nine months of 1997, the drop-out rate jumped to 31.3 percent (3,010 drop-outs in 9,626 repaid loans). The lender was interested in scoring because it wanted first to identify at-risk segments of its clientele and second to identify individual at-risk borrowers while they still had a loan outstanding.

2.3 Scoring

Scoring assumes that the relationship between the risk of drop-out and the characteristics of a borrower and lender will be the same in the future as in the past. For example, suppose 16 percent of loans to traders were not renewed and 20 percent of loans to manufacturers were not renewed. A simple scoring model would then predict a 16-percent risk of drop-out for traders and a 20-percent risk for manufacturers.

The scoring model developed here relates drop-out risk to eight characteristics. The relationships are derived with a logit model based on the drop-out behavior of loans repaid through 1996. An out-of-sample test checks how well scoring would have predicted drop-out for loans repaid in 1997.

2.4 Model

Logit is appropriate because the dependent variable is dichotomous, zero for drop-outs and one for repeats. Logit is preferred to its main alternative—discriminant analysis—for four reasons.[3] First, logit estimates how each individual characteristic affects risk. Second, logit predicts risk directly as a probability. Third, logit does not require strong distributional assumptions. Fourth, logit predicts as well as discriminant analysis but is easier to use and interpret (Turvey, 1991; Wiginton, 1980).

2.5 Variables

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[2] *Good borrowers* have arrears of less than 30 days. Attrition is not a concern for bad borrowers (arrears of 30 days or more) because the lender—as policy—kicks them out.

[3] Viganò (1993) uses discriminant analysis to score arrears at an African microlender.

The scoring model takes drop-out risk for each loan as a function of eight variables. This paper does not develop a detailed theoretical model for two reasons. First, the data set is very limited. Second, scoring models differ from other regression models in that the principle aim is not to test hypotheses about estimated coefficients but rather to predict risk. If a variable boosts predictive power, then it is included.[4]

Loan size. If competing lenders are willing to make larger loans, then borrowers with smaller loans might be more likely to drop out.

Gender. If females have more alternative sources of financing than males, then they may drop out more. If they have fewer alternatives, then they may drop out less.[5]

Sector. Traders may be less likely to drop out because they continuously finance inventory. Manufacturers might borrow to purchase a fixed asset and then drop out because they no longer want loans. Furthermore, lenders may compete more for manufacturers if their larger, longer loans are more profitable.

Experience of the borrower. Newer borrowers might drop out more if they are testing the waters or if they can switch lenders with less loss of reputation capital.

Arrears. The lender kicks out borrowers with spells of arrears of 30 days or more, but drop-out might increase even for borrowers with shorter spells of arrears if borrowers themselves suffer when they fall behind.

Loan officer. Drop-out varies across loan officers, partly due to differences in skill and effort in managing clients and partly due to differences in the socio-economic environment of the beat assigned to a given loan officer.

Experience of the loan officer. Greater experience (in terms of numbers of loans disbursed) might impart skills that help to retain good borrowers.

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[4] For the same reason, noisy data are still useful as long as they add predictive power.

[5] In some countries, it is illegal to include gender in a scoring model.

Branch. Drop-out varies across branches, just as across loan officers.

Ideally, the scoring model would also include age, education, and length of residence of the borrower; ownership of a telephone, house, or car; measures of the size and financial strength of the household and firm; and other terms of the loan contract such as length, frequency of installments, and guarantees. These data are not available. Thus, the test here is conservative: if a limited model can predict drop-out to some extent, then a full model would probably be even more powerful.

3. Estimated effects

This section reports how specific characteristics affect drop-out risk. Lenders can use this knowledge to adjust products and policy to manage drop-out better.

3.1 Regression results

The log-likelihood for the logit model based on 37,982 loans repaid through 1996 was !17,355. The model differed from an intercept-only model with p = 0.01. Of 77 estimated effects, 62 differed from zero with at least 90-percent probability.

Tables 1 to 3 display sample means, effects on drop-out risk (in probability units) of a unit change in a variable, and p-values of the effects.[6] The dependent variable is zero for drop-outs and one for repeats, so negative effects increase risk of drop-out. The logit coefficients do not have direct interpretations and are omitted.

3.2 Amount disbursed

The mean amount disbursed (in 1998 dollars) in the sample was $675 (Table 1). All else constant, borrowers with larger loans were less likely to drop out; each additional dollar was associated with a 1.7 basis-point reduction in risk (p = 0.01).[7] Thus, a $100 increase in loan size meant a 1.7 percentage-point decrease in risk. Given drop-out rates of 18.3 percent (1988-6) and 31.3 percent (1997), this is a large effect.

In a competitive market such as Bolivia, borrowers with small loans may be able to find another lender willing to make larger loans. Borrowers who already have larger loans may already be satisfied and thus are less likely to drop out. The Bolivian lender studied here might try to reduce drop-outs by making larger loans, although of course this might also increase arrears.

3.3 Gender

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[6] All the results in the three tables come from a single logit regression.

[7] A *basis point* is one percent of one percent, or 1/10,000 = 0.0001.

About 42 percent of loans went to males, and 58 percent went to females (Table 1). All else constant, females were 1 percentage point (99 basis points) more likely to drop out (p = 0.03). The lender might discuss this result with loan officers and with female clients. The appropriate response depends on whether females drop out because they can do better elsewhere or because they no longer want loans.

3.4 Sector

Manufacturers received 47 percent of loans, and traders 53 percent. All else constant, traders were 3.5 percentage points (348 basis points) less likely to drop out.

Perhaps the lender's products and services are better suited to traders, or perhaps manufacturers are less likely to want repeat loans. In the first case, the lender might investigate why manufacturers are less satisfied; in the second case, the lender might visit manufacturers with loans outstanding to encourage them to repeat (perhaps with incentives such as larger loans, longer terms, or lower interest rates).

3.5 Client experience

A set of dummies represents the number of past loans (Table 1). About 46 percent went to new borrowers. Drop-out risk generally fell with experience. The effects were large and statistically significant; for example, compared with a new borrower, someone with two past loans was 6.4 percentage points less likely to drop out.

This probably reflects two factors. First, many new borrowers discover that they dislike indebtedness. Second, as borrowers demonstrate their creditworthiness over several loans, the lender can tailor loan terms—disbursements, installments, and terms to maturity—to client demand. This makes the switch to other lenders—who cannot immediately tailor their loans as well—less attractive.

3.6 Arrears

About 55 percent of loans had no arrears (Table 1). Even for short spells, however, more arrears meant more drop-out.[8] For example, compared with two days, seven days increased risk by 1,698 ! 278 = 1,420 basis points (14 percentage points).

Two factors drive this effect. First, borrowers dislike the stress of arrears. Trouble in the current loan signals greater risk of trouble in the next loan and so may increase drop-out. Second, improvements in loan terms (larger disbursements, less-frequent installments, longer terms to maturity) depend on prompt repayment. If arrears stall improvements in loan terms, then some borrowers may drop out.

3.7 Loan officers

The heart of microlending to individuals is the loan officer (Rodríguez-Meza, 2000; Churchill, 1999). The officer screens applicants, monitors repayment, and duns late payers. Loan-officer pay often depends largely on incentives based on the size and performance of their personal portfolio (Holtmann, 2001).

Table 2 ranks specific loan officers by risk. The omitted category ("other") includes all officers with less than 300 loans. Effects were large; for example, compared with clients of officer 2, clients of officer 37 were more likely to drop out by 677 ! (!900) = 1,577 basis points (about 16 percentage points). Some of this may be due to differences in skill and effort, and some may be due to differences in loan-officer beats that are not captured in the model.

Some star loan officers have low risk and account for large shares of disbursements. For example, officers 2 and 3 had very low risk of drop-out, and each

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[8] A curious exception is that, compared with no arrears, one day of arrears *decreases* drop-out risk. Perhaps borrowers with no arrears are people who dislike indebtedness intensely, or perhaps those with one day of arrears find out that the cost of being in arrears was not as high as they feared and so become more willing to borrow again. In any case, the risk of drop-out increases with each day of arrears after the first.

accounted for more than 6 percent of loans. Other officers are underachievers and may be logical targets for special training or incentives. Examples are officers 34, 37, 38, and 39, all of whom had large shares of disbursements but high drop-out risk.

3.8 Loan-officer experience

The average loan officer had 606 loans of experience (Table 3). Experience had no consistent effect on drop-out. In the range from 0 to 100 loans and 101 to 500 loans, additional disbursements increased drop-out risk, but the effects were not statistically significant. From 501 to 1,000 loans, risk decreased, but risk then increased for 1,001 to 1,500 loans before again becoming insignificant for loans above 1,500.

3.9 Branches

As with loan officers, some branches retained borrowers better than others (Table 3). All the branch effects were large. Compared with the central office and small branches, the best retainer (Oruro) decreased risk by almost 21 percentage points. As with loan officers, the Bolivian lender might use training and/or incentives to manage drop-out risk associated with a given branch.

3.10 Discussion

For the Bolivian microlender studied here, drop-out risk was higher for small loans, women, manufacturers, newer borrowers, and those with more arrears. Risk also depended on the specific branch and loan officer.

This knowledge can help a lender to adjust products and policies to attract more repeat business. An example is training targeted to high-risk branches or loan officers. A lender might also conduct market research with at-risk segments of the clientele to discover whether they switch to competitors—and why—or whether they simply no longer want loans. In this way, scoring can be useful even if a microfinance lender never uses it to predict drop-out risk for individual borrowers.

4. Predictive power

This section uses an out-of-sample test to check how well the model based on data through 1996 would have predicted in 1997.

4.1 Mechanics of prediction

Scoring assigns a weight (a score) to characteristics. The scores (the effects in Tables 1-3) are derived from historical relationships between characteristics and drop-out. Predicted risk is the sum of the scores.[9] For example, suppose a female trader has no arrears in her $700 second loan from loan officer 26 at branch El Alto. The base risk is 0.2709, or 2,709 basis points.[10] Each dollar disbursed decreases risk by 1.7 basis points, so $700 decreases risk by 1,190 basis points. Being female adds 99 basis points, and being a trader subtracts 348 basis points. Being a second-time borrower decreases risk by 354 basis points. Not having arrears has a weight of zero. Loan officer 26 decreases risk by 122 basis points, and branch El Alto decreases risk by 389 basis points. All together, the predicted risk of drop-out for this loan is 2,709 ! 1,190 + 99 !348 ! 354 + 0 ! 122 ! 389 = 405 basis points (about 4 percentage points).

4.2 Evaluation of predictive power

4.2.1 Predicted versus realized risk

The simplest test compares predicted risk from scoring (before drop-out behavior is known) with realized risk from observed behavior. Scoring has *absolute power* if x percent of cases with x percent predicted risk do drop out. Scoring has *relative power* if cases with low predicted risk drop out less than cases with high predicted risk.

Scoring for the Bolivian lender had relative power (Figure 1). Realized risk was

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[9] In logit, predicted risk is not a linear function of individual effects, but a linear formula is used in the example here for simplicity.

[10] The logit intercept is !0.99, and the logit formula $e^{!0.99}/(1+e^{!0.99})$ gives 0.2709.

higher as predicted risk was higher. For example, 15 percent of cases with a 10-percent predicted risk dropped out, versus 30 percent of cases with a 40-percent predicted risk.

The correlation between realized risk and predicted risk, while positive, was not perfect, so scoring lacked some absolute power (Figure 1). For example, realized risk was higher than predicted for low-predicted-risk cases, and realized risk was lower than predicted for high-predicted-risk cases. In the range from 20 to 25 percent, however, predicted risk did match realized risk. Many cases fell in this range, as realized risk through 1996 was 18.3 percent. Weak absolute power in the tails of the distribution is not surprising given that the sharp, unprecedented changes in the Bolivian microfinance market in 1997 are not well reflected in the eight variables in the model.

4.2.2 Classification by thresholds

In practice, lenders would set a policy for cases with predicted risk above a chosen threshold. For example, a lender might instruct loan officers to visit good clients—before their final installment—if predicted risk of drop-out exceeds x percent.

Before a loan is repaid and drop-out status revealed, cases with predicted risk below a given threshold are expected to repeat and are classified as *positives*. Cases with predicted risk above a threshold are expected to drop-out and are classified as *negatives*. After a loan is repaid, there are four possible outcomes (Table 4). A *true positive* is a predicted repeat who in fact repeats. Likewise, a *true negative* is a predicted drop-out who in fact drops out. A *false positive* is a predicted repeat who drops out, and a *false negative* is a predicted drop-out who repeats.

In the 1997 test sample, 3,010 borrowers dropped out, and 6,616 repeated. Based on the scoring model here, Table 5 lists the four classes for a range of thresholds for the Bolivian microlender. For example, a threshold of 80 percent leads to 6,196 true positives (who would have repeated even without a "preventive" visit) and 741 true negatives (for whom a visit might have prevented drop-out). At the same time, the lender would not visit 2,269 false positives who did drop out, and it would waste time and incentives on visits to 420 false negatives who would repeat anyway.

4.2.3 Optimal thresholds

With higher thresholds, true positives increase, but true negatives decrease. The optimal threshold depends on the trade-offs between expected costs and benefits (financial and non-financial) of correct and incorrect predictions. In general, the optimal threshold is not 50 percent. Let $ be the benefit of correctly identifying cases who, without extra encouragement, would drop-out (true negatives), remembering that some of these cases will drop out even with extra encouragement. Let (be the cost of a "preventive" visit to a client predicted to drop out (negatives). The net benefits from scoring (once installed) are the benefits of visiting true negatives net of the costs of visiting all negatives:

(1)
FUNC{Net~Benefits}~=~$`@`FUNC{True~negatives}~!~(`@`(`FUNC{True~negatives ~+~False~negatives}`)`.

Setting the left side of Equation 1 to zero and rearranging gives the optimal threshold as the point where the ratio of true negatives to false negatives equals the ratio of the cost of a visit to the benefit (net of costs) of a visit to a true negative:

(2)
{(} OVER {$~!~(}~=~{FUNC{True~negatives}} OVER {FUNC{False~negatives}}`.

For example, suppose that the Bolivian microlender had $ of $83 and (of $50 so that (/($!() = $50/($83!$50) Ñ 1.51. Given the outcomes in the out-of-sample test (Table 5), the optimal threshold is 70 percent because there the ratio of true negatives to true positives is 885/591, or about 1.50.

5. Conclusion

Can scoring help microfinance lenders to manage drop-out? The results here for a lender in Bolivia suggest that it can. Risk of drop-out is greater for women, manufacturers, newer borrowers, and those with more arrears. Risk also depends on the branch and loan officer. Armed with such knowledge, a lender might adjust programs and policies to attract more repeat business. Out-of-sample tests also suggest that scoring can identify individual borrowers who are at-risk of drop-out even before they repay their current loans. A lender could then visit them and encourage them to repeat.

Sophisticated management aids such as scoring for drop-out are appearing first in microfinance markets where competition has led to intense pressure to innovate. Data requirements for scoring, however, are high, and scoring may be impractical for microlenders who have not have data on many past loans. Still, just as scoring became pervasive in almost all types of lenders in high-income countries (Mester, 1997), scoring may become common among the largest microlenders in low-income countries.

Of course, scoring is not a panacea. Although it has some predictive power, it cannot predict all drop-outs. Furthermore, some borrowers drop out not because they are dissatisfied but because they no longer want loans. Although some lenders might prefer that all clients borrow indefinitely, drop-outs due to "graduation" are a healthy sign that microfinance has had a positive social impact.

Notes

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Table 1: Effects of the amount disbursed and of borrower characteristics on drop-out risk

Table 2: Effects of the loan officer on drop-out risk

Table 3: Effects of the experience of the loan officer and of the branch on drop-out risk

Table 4: Four possible results of comparison of predicted drop-out with realized drop-out

		Predicted	
		Positive (repeat)	Negative (drop-out)
Realized	Repeat	True positive: Predicted to repeat, and repeats	False negative: Predicted to drop out, but repeats
	Drop-out	False positive: Predicted to repeat, but drops out	True negative: Predicted to drop out, and drops out

Table 5: Comparison of predicted drop-out with realized drop-out in an out-of-sample test

Figure 1: Predicted risk versus realized risk