The Risk of Exit by Borrowers from a Microlender in Bolivia

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Abstract

I model the risk that borrowers will not renew their loans from a microlender in Bolivia. Exit risk is greater for newer borrowers, women, manufacturers, and those with more past arrears. Risk also depends on the amount disbursed, the loan officer and the branch, and the time since the first loan. Although the knowledge of quantitative characteristics cannot replace knowledge of qualitative character, the model predicts well enough out-of-sample to help lenders to know where investments in relationships with specific borrowers are most likely to curb the risk of exit most.

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1. Introduction

In high-income countries, credit-card lenders judge risk with statistical models based on a few simple traits such as home ownership, income from formal wage employment, and past repayment as recorded by a credit bureau (Mester, 1997; Lawrence, 1992). Credit-scoring allows credit-card lenders to make massive numbers of small, uncollateralized loans each day without the costs of individual evaluations of risk. According to Lewis (1990, p. 138), scoring "is a standard procedure almost anywhere credit is granted on a large scale."

Like credit-card lenders in high-income countries, microlenders in low-income countries make massive numbers of small, short, unsecured loans. Borrowers from microlenders cannot get other formal loans because they do not have traditional collateral nor formal wage employment and thus cannot signal their risk in ways that lenders can process at a low cost. As far as I know, however, no microlender uses credit-scoring even though the central tasks of microlenders are the same as those of scoring models: to judge risk, to detect factors that affect risk, and to design contracts and policies to control risk.

Can scoring help microlenders? To find an answer, I model the risk of exit by borrowers from a microlender in Bolivia. Borrowers exit when they do not get a new loan after they repay their old one. Exit is greater for new borrowers, women, manufacturers, and those with more past arrears. Risk also depends on the time since the first loan, the amount disbursed, and the loan officer and branch. In out-of-sample tests, the model here predicts much better than a naïve model.

Scoring can help microlenders, but the knowledge of a few simple quantitative characteristics cannot substitute completely for the knowledge of qualitative character and cash flows that loan officers build through long-term close contact with borrowers. Still, the results here suggest that scoring can help to detect high-risk cases. A microlender could use the model, for example, to ask loan officers to pay an extra visit to those borrowers with the highest predicted risk of exit.

Section 2 below discusses the problems and prospects of scoring for microlenders. Section 3 describes microlending in Bolivia, the data, and the model. Section 4 reports the statistical results, and Section 5 tests out-of-sample prediction. Section 6 concludes the paper.

2. Microlending and scoring

Microlenders have not adopted scoring so far for four reasons. First, low-income countries lack credit bureaux, and most borrowers of microlenders are self-employed. In credit-card models, the credit record and wage employment are the strongest predictive factors. Second, many risks faced by the self-employed poor are not highly correlated with simple-to-observe personal traits. Scoring requires at least some correlation. Third, the best microlenders predict risk from subjective knowledge of borrowers acquired by loan officers through repeated close contact. In contrast, scoring starts from the premise that risk can be predicted from objective traits that a stranger can observe in a one-shot contact. Fourth, most microlenders are young, small, and growing. Scoring requires data from a big, stable population. These stylized facts of microlenders limit the maximum possible effectiveness of scoring but do not preclude the possibility of some effectiveness, albeit less than in high-income countries.

2.1 Strengths

Scoring has four strengths. First, it can cut the time to evaluate applications. When predicted risk is very high or very low, management might summarily accept or reject. More resources would go to borderline cases and to overrides where the loan officer knows something that the model does not.

A second strength of scoring is to make risk more directly susceptible to policy. For example, a lender who wants to expand might tell loan officers to loosen standards, but each officer will act on this in his or her own way. In contrast, a lender with a scoring model could reduce the cut-off threshold a given number of percentage points and know the likely increase in accepted applicants as well as the likely increase in risk.

Third, scoring can make judgements of risk more consistent, both inter-officer and intra-officer. Automation may also reduce the wage bill because officers can be less well-qualified and because apprenticeships can be shortened (Lewis, 1990). The wage bill is a key factor in growth and profit for microlenders (Rhyne and Rotblatt, 1994).

Fourth and most important, scoring models can be tested. This soothes the fears of managers and loan officers who doubt that a computer can help to do their job. Microlenders took a long time to learn to judge the risk of small, short, unsecured loans, and they have reason to be leery of attempts to graft a new part into a system that works on fundamentally different principles.

2.1 Weaknesses

For microlenders, scoring has seven weaknesses. First, models degrade as niches shift, competition changes, and policies evolve. Scoring assumes that the future will be like the past, so it cannot predict what has not already happened many times. Thus scoring will miss risk due to unprecedented changes in the market or in lender policy. It also misses risk correlated with unobserved or unrecorded variables.

Second, scoring requires many cases of both good and bad outcomes. Many microlenders are too small, too young, or too paper-based to have the data needed.

Third, scoring technique, while simple, is not well-known. The firms that sell models guard their trade secrets, so, except for Greene (1998 and 1992) and Boyes *et al.* (1989), the academic literature is weak. Model development and implementation requires skill not only in statistics and finance but also in project management.

Fourth, each lender needs its own model because each has its own niche and technology. One size does not fit all.

Fifth, the use of traits such as sex, age, ethnicity, and marital status may be unethical if not illegal. These traits are often excellent, inexpensive predictors of risk, but of course it is unfair to judge people by traits that they did not choose.

Sixth, even if scoring can judge risk well, a lender may not have effective ways to affect risk. For example, a lender may be powerless to convince a known high-risk borrower not to exit. This is not a drawback of scoring itself; most lenders would prefer to know risk and to have their hands tied than not to know risk at all.

In principle, both the problems and the prospects for scoring in microlending are great. The rest of this paper tests scoring in practice for a Bolivian lender.

3. A model of exit at a lender in Bolivia

This section describes the market for microlending in Bolivia, the data, and the econometric model.

3.1 Microlending in Bolivia

Bolivia is the cradle of microlending in Latin America. Despite sparse population—6 people per km^2—deep poverty, and rugged topography, microlending has a very high rate of penetration (Navajas *et al.*, 2000). Most Latin American countries have, at most, one microlender with more than 10,000 active borrowers; Bolivia has a dozen this big. Three have converted from unregulated not-for-profits to regulated for-profits, and several more hope to convert soon. The lenders work in both rural and urban areas and with both individuals and groups. In La Paz, most borrowers are near the poverty line but are not among the poorest.

Profits attracted competition from Bolivian banks and from Chilean consumer-finance companies. In the battle for market share, lenders started to advertise, to open new branches, and to tempt borrowers from other lenders to switch. The pace quickened in 1997; exit rates skyrocketed, and arrears doubled. Not only did tolerance of arrears by the consumer-finance companies weaken the culture of repayment, but borrowers also took loans from more than one lender. The economic crisis in Brazil in 1999 also affected repayment from the women traders who are the bulk of the microlending portfolio in Bolivia.

3.2 The data

The microlender studied here serves individuals in trade and manufacturing in urban areas. It evaluates risk almost exclusively on the personal judgement of loan officers; most loans are not collateralized, and a committee discusses only very big or unusual loans. From birth in August 1988 until the end of 1996, the exit rate was 21 percent, defined as the number of borrowers who did not get new loans (8,490) divided by the number of loans paid off (39,956). In the first nine months of 1997, the exit rate jumped to 36 percent (3,761 exits from 10,555 loans repaid).

The data include the following for each loan disbursed through Sept. 31, 1997:

- Date of disbursement;
- Amount disbursed;
- Sex of borrower;
- Sector of firm;
- Type of guarantee;
- Number of past spells of arrears;
- Length of longest spell of past arrears;
- Branch;
- Loan officer;
- Whether the loan was outstanding on Dec. 31, 1996 or Sept. 30, 1997.

This list of variables is extremely short. At the least, most scoring models would also include the age, education, and length of residence of the borrower; ownership of a telephone, house, or car; and measures of the size and financial strength of the household and firm. Thus this exercise is a conservative test: if a truncated model can predict the risk of exit, then a full model might be even more powerful.

3.3. The statistical model

The structural random-utility model follows Greene (1993). The unobserved (1 x N) vector of expected benefits b_b to borrowers of the choice to go bad (to exit) is a linear function of an unobserved (k x 1) vector of coefficients γ_b, an observed (k x N) matrix of independent variables U_b, and an unobserved (1 x N) vector of errors ϵ_b:

$$b_b = \gamma_b' U_b + \epsilon_b. \tag{1}$$

Likewise, the unobserved expected costs c_b of the choice to go bad is

$$c_b = \delta_b' W_b + \mu_b. \tag{2}$$

The choice to stay good (to repeat) has expected benefits b_g and expected costs c_g. Borrowers are observed to go bad ($y = 1$) when the unobserved net benefit of exiting minus the net benefit of repeating (y^*) is positive:

$$\begin{aligned} y = 1 \Leftrightarrow y^* &= (b_b - c_b) - (b_g - c_g) \\ &= (\gamma_b' U_b - \delta_b' W_b - \gamma_g' U_g + \delta_g' W_g) + (\epsilon_b - \mu_b - \epsilon_g + \mu_g) \\ &= \beta' X + \epsilon \\ &> 0. \end{aligned} \tag{3}$$

The logit model assumes that ϵ has a logistic distribution with mean zero and variance one and a cumulative distribution function $\Lambda(z) = \exp(z)/[1+\exp(z)]$. The maximum-likelihood estimator chooses a (k x 1) vector β^* to maximize

$$\ln L = \sum_{i=1}^{N} \ln \Lambda [\beta' X_i (2 y_i - 1)]. \tag{4}$$

For borrower i, the estimated risk of exit $E[y_i]$ is $\Lambda^* = \Lambda(\beta^{*\prime}X_i)$. At the means of the 1988-1996 sample, $\Lambda^* = 0.1691$. The change in the probability of exit due to a small change in a continuous independent variable is $\partial E[y]/\partial X = \Lambda^* \cdot (1 - \Lambda^*) \cdot \beta^*$. Dummy variables are not continuous, but the estimated probability of exit due to a switch in a dummy from 0 to 1 is usually quite close to the effect from the continuous formula.

A consistent estimate of the marginal effects replaces X with $\bar{x}$, a ($1 \text{ x } k$) vector of the sample means of the independent variables. Given a consistent estimate of V, the ($k \text{ x } k$) covariance matrix of β^*, the standard error of the effects is asymptotically normal and is the square root of the diagonal of $\lambda q V q'$, where $\lambda = [\Lambda^* \cdot (1 - \Lambda^*)]^2$, $q = I + (1 - 2\,\Lambda^*) \cdot \beta^* \bar{x}$, and I is a ($k \text{ x } k$) identity matrix. The analysis focuses not on the estimated coefficients but rather on the marginal effects because estimated risk depends non-linearly on all independent variables and on all estimated coefficients.

The logit model avoids the weaknesses of the discriminant model used in most published scoring models, including the only known scoring model for borrowers in a bank aimed at the poor in a low-income country (Viganò, 1993). Besides its small sample ($n = 100$), the model of Viganò has three drawbacks common to all discriminant models (Eisenbeis, 1981). First, it makes the unlikely assumption that the distribution of independent variables is joint-normal and differs between the good cases and the bad cases only in the mean. Second, the estimated coefficients have no direct interpretation. Third, discriminant models do not estimate risk as probabilities.

4. Estimated effects

This section discusses the estimated effects on exit due to changes in independent variables. Although microlenders want to predict the risk of exit, they also want to know the factors that influence it to guide changes to technology and policy.

The model uses all loans paid off from August 1988 to the end of 1996. I used loans paid off from Jan. 1 to Sept. 30, 1997 to test out-of-sample prediction (Section 5).

The Chi-square statistic for comparison with a model with only an intercept was significant at 0.0001. Of 120 estimated coefficients, 70 differed from zero with at least 90-percent probability. Statistical significance, however, does not necessarily imply predictive power (Hand, 1994; Greene, 1993; Wiginton, 1980).

4.1 Experience of the borrower

4.1.1 Number of past loans

With a set of dummies for the number of past loans that the borrower has had, my model is like a discrete-event hazard model with a non-parametric baseline (Jenkins, 1995). Estimated logit coefficients for each stage, the estimated effects of advancement, and standard errors and p-values are in Table 1.

The estimated coefficients are highly significant, and they become more negative as the number of past loans increases (middle three columns of Table 1). Negative coefficients tend to increase the probability of repeats ($y_i = 0$), and positive coefficients tend to increase the probability of exit ($y_i = 1$). More past loans means less future exit.

How big is the effect of an additional loan? The estimated changes in probabilities (rightmost three columns of Table 1) are large and statistically significant. Compared with a new borrower, a borrower with 10 loans or more is 30 – 11 = 19 percentage points less likely to exit. First-time borrowers are more likely to misjudge the net gains of borrowing and thus to drop out after a quick test, and repeat borrowers are less likely to want to start from scratch with a new lender.

4.1.2 Months since the first loan

The number of past loans does not capture all the nuances of experience because a borrower might, for example, get three one-month loans or three one-year loans. I measure time as a borrower with a set of dummies defined as the bounds on the integer part of the natural logarithm of one plus the number of months since the first loan.

Most borrowers have 0-6 months of experience. Exit decreases for 7-19 months, increases for 20-53 months, and increases even more for 54-147 months. Only this last effect is both precise and large. Independent of the number of past loans, the risk of exit increases with the time since the first loan. Why would this be? All first-time borrowers want to borrow. As time passes, however, the chances that they want repeat loans must decrease as the forces that affect their demand change.

4.2 Past arrears

I measure past arrears as the longest spell in days and as the number of spells in the previous loan (Table 2). Spells of arrears were common, but most were very short.

To avoid perfect collinearity with the number of past loans, I count first-time borrowers as if they had no arrears in the past.

4.2.1 Longest spells

Compared with borrowers with no arrears, borrowers were less likely to exit if their longest spell lasted 1-4 days and more likely if their longest spell lasted 5 days or more. The effects are precise and large; one day of arrears decreases the probability of exit by 6 percentage points, and 29 or more days increases it by 41 percentage points.

It makes sense that very long spells prompt exit—borrowers do not like the anguish of delinquency and lenders do not like the costs of default. The lender does not, however, have a rule to kick out all borrowers past some level of arrears. Still, some borrowers who do not repeat are not drop-outs but kick-outs.

But why would a short spell be better than no spell at all? The result is not due to counting first-time borrowers as having had no arrears in their non-existent previous loan; the same pattern remains in a regression with just dummies for arrears.

The result may very well be due to data errors or to spurious correlations between arrears, exit, and omitted variables, but it also may be real. There are plausible stories why short spells of arrears might reduce exit more than no spells.

For example, 85 percent of loans had no spells longer than a week, and the lender does not seem to worry about these very short spells. Some borrowers pay late not because they cannot pay or do not want to pay but because they wait until they can combine a trip to the branch with other errands or because they need time to collect cash from their own customers. Also, compared with borrowers nervous about making each payment on time, borrowers who learn that they can pay a few days late without punishment are more at ease with debt and thus more likely to get a new loan.

4.2.2 Number of spells

With length held constant, the number of spells of arrears has a large, precise, and increasing effect on the risk of exit (Table 2). Compared to someone with no spells, someone with nine or more spells is 16 percentage points more likely to exit. Even if all spells are short, both borrower and lender want to avoid the costs of late repayments.

4.3 Sex and sector

Most loans went to women (Table 3), but women were 1 percentage point more likely to exit than men. Traders, regardless of their sex, are 2 percentage points less likely to exit than manufacturers. Changing sectors between loans had a similarly big effect, but the estimate is imprecise and only 0.6 percent of borrowers switched sectors.

4.4 Amount disbursed

Exit might depend on the level, the increase, or the decrease in the amount disbursed. In terms of constant dollars as of the end of 1998, each $100 disbursed decreases risk by 0.2 percentage points (Table 3). Exit decreases by 0.7 percentage points for each $100 increase between loans, where the increase is zero for first loans and for loans smaller than the previous loan. A decrease of $100 increases risk by 0.1

percentage points. Big loans and bigger loans decrease exit. The lender, however, might not want to adjust loan size to retain more borrowers because bigger loans have more default risk and because the effects of loan size on exit are small. Also, the average loan ($700) and the average change ($140 for increases and $25 for decreases) are small.

4.5 Guarantees

None of the four guarantees accepted by the microlender has a large, precise effect on exit (Table 3). Likewise, changes in the guarantee between loans have no effect. Microlenders rely less on collateral than on the sixth sense of loan officers.

4.6 Loan officers

The heart of microlending is the relationship of the loan officer to the borrower. Compared with “other” officers with less than 80 loans paid off, the best retainer decreased exit by 14 percentage points, while the worst retainer increased exit by 13 percentage points (Table 4). Many effects are large and precise, and lenders may have wide scope to influence them through incentive schemes and training.

Twelve percent of borrowers switch loan officers between loans, often because a loan officer quits or is fired. This increases risk by 1 percentage point (Table 4).

Compared with new loan officers, exit is higher for officers with 2-6 months of experience and still higher for 7-19 months (Table 5). Although some estimates are imprecise, officers seem to take good care of their first customers but slacken as their portfolios expand. Once mature, officers seem to focus again on quality rather than quantity, so risk falls for 20-53 months and still more for 54-147 months.

4.7 Branches

Some branches retain borrowers better than others (Table 5). Compared with "other"—the central office and four small branches—the best retainer decreased exit by 23 percentage points, and the worst increased it by 3 percentage points. Lenders may be able to influence risk at the branch level. This lender may also want to track borrowers who switch branches because it increases exit by 4 percentage points.

4.8 Date of disbursement

To control for seasonal or one-shot changes in the market or lender policy, I included a set of dummies for the year and month of disbursement. Exit in 1992-1996 was less than in 1988-1991, hitting bottom in 1994 and then increasing (Table 6). The only precise month effect is a decrease in exit for loans disbursed in Bolivian winter.

In sum, exit risk depends mostly on borrower experience, past arrears, and the loan officer and branch. The date of disbursement also has a big effect. Factors with smaller effects include sex, sector, and the amount disbursed. Once a lender has approved a new borrower, most of the most important factors—except for the effort and skill of the branch and the loan officer—are beyond its scope of influence.

5. Predictive power

The purpose of a scoring model is to predict risk outside the sample used to make it, to use what is known of the past to guess what will happen in the future. Here, I check how well the model built with 1988-96 data classifies borrowers who repaid loans and then exited or repeated in the first nine months of 1997.

Cases with estimated risk above a threshold are classified as bads (exits), and cases below it are classified as goods (repeats). Classification has four possible outcomes. A *true positive* is when the model predicts a known good as good. Likewise, a *true negative* is when the model predicts a known bad as bad. A *false positive* is a known bad predicted as good, and a *false negative* is a known good predicted as bad.

The top four rows of Table 7 list the cases in each outcome for 11 thresholds. A threshold of zero is an all-bad naïve model; estimated risk is always above the cut-off. In the test sample, 3,761 (36 percent) were known bads (with a zero threshold, all true negatives) and 6,794 (64 percent) were known goods (with a zero threshold, all false negatives). As the threshold moves up, the number of true positives increases and the number of false negatives decreases; however, false positives also increase, and true negatives also decrease. A threshold of one is an all-good naïve model; estimated risk is always below the cut-off. Because movements of the threshold trigger trade-offs among the four outcomes, the optimal threshold depends on the gains and costs of mistakes and of correct guesses and thus on the goals of the lender.

5.1 Sample separation

Does the model separate goods from bads? One way to check is the population-weighted probability distributions of estimated risk for known goods (Figure 1) and for known bads (Figure 2). For known goods, estimated risk is skewed left with a thin right tail (mean 0.206, median 0.158). For known bads, estimated risk is more uniform with modes in both tails (mean 0.443, median 0.368). Thus most cases with high (low) estimated risk were in fact bad (good).

The cumulative distribution functions (Figure 3) also show a clear separation. At all points, the distribution of known goods is to the left of that of known bads.

Finally, the drop-out rate was 21 percent in 1988-96 and 36 percent in 1997. A naïve prediction for the 1997 rate would have been 21 percent, but the model predicted 29 percent. Thus half the increase in drop-outs was due to changes in traits in the model. Scoring does separate goods from bads, at least to some extent.

5.2 True rates

How well does the model separate? A lender would measure separation with either true rates or predictive values (Hand, 1994; Kennedy, 1998). True rates are the share of known goods (bads) predicted as goods (bads). The *true positive rate* is the share of known goods predicted as goods, true positives / (true positives + false negatives) (middle three rows of Table 7). In Figure 1, this is the area left of the threshold divided by the total area. Likewise, the *true negative rate* is the share of known bads predicted as bads, true negatives / (true negatives plus false positives). In Figure 2, this is the area right of the threshold divided by the total area.

For a range of thresholds, Figure 4 shows the true positive rate, the true negative rate, and the *true total rate*, all trues divided by the size of the test sample. For thresholds above 0.21, the true positive rate for the scoring model beats the all-good naïve model (64 percent). Below 0.56, the true negative rate of the scoring model beats the all-bad naïve model (36 percent). The true total rate exceeds the highest naïve rate for thresholds above 0.19, with the greatest difference at a threshold of 0.45.

Figure 5 shows the trade-off between the true positive rate and the true negative rate. The diagonal line is the trade-off in a naïve model that predicts some fixed percentage as good. The scoring model has more power as its curve contains more area above the diagonal; a perfect model would trace the upper and right borders, classifying all known goods as goods and then all known bads as bads (Hand and Henley, 1997). In fact, the scoring model is near the upper border for true positive rates below 0.5, and near the right border for true negative rates below 0.2. For thresholds near zero (one), the model hits a large share of goods (bads) and misses a small share of bads (goods).

5.3 Predictive value

A lender might also judge a model by its predictive value, the share of predicted goods (bads) that are goods (bads). The *positive predictive value* is the share of predicted goods that are known goods, true positives / (true positives + false positives) (bottom three rows of Table 7). This is the area left of the threshold in Figure 1 for known goods divided by that same area plus the area left of the threshold in Figure 2 for known bads. The *negative predictive value* is the share of predicted bads that are known bads, true negatives / (true negatives plus false negatives). This is the area right of the threshold in Figure 2 for known bads divided by that same area plus the area right of the threshold in Figure 1 for known goods.

For a range of thresholds, Figure 6 shows the positive predictive value, the negative predictive value, and the *total predictive value*, equal to the total true rate. The all-good naïve model has a positive predictive value of one, a negative predictive value of zero, and a total predictive value of 0.64. Conversely, the all-bad naïve model has a positive predictive value of zero, a negative predictive value of one, and a total predictive value of 0.34. The scoring model has a higher total predictive value than the best naïve model for thresholds above 0.19, with the greatest difference at 0.45.

By all measures, the scoring model predicts exit well. Its power is even more remarkable because a lot of exit in 1997 was due to unprecedented change in the market and because the model uses a small subset of the simple-to-observe data that lenders often collect.

6. Conclusion

Models that predict risk from traits of the borrower, the lender, and the loan are a common way to reduce the costs of credit-card lenders, the microlenders of high-income countries. But microlenders in low-income countries do not yet use scoring.

Can scoring help microlenders? The model here pinpointed a host of factors that affect the likelihood of exit at a microlender in Bolivia. Furthermore, in out-of-sample tests, the model predicts exit much better than naïve models.

In microlending, knowledge of characteristics from computers will not replace knowledge of character and cash flows from personal contact. Scoring does, however, show some promise as a way to mark which cases to check first. Most uses in practice will probably focus on borrowers whose predicted risk is either very high (super-fails) or very low (super-passes). For example, a lender might give loan officers a list each month of the 10 borrowers in their charge who are most likely to exit and who thus might deserve an extra visit or more encouragement.

Much work on scoring for microlending remains. Lenders will likely want to model default, and they may also want to estimate the risk that a borrower x days in arrears now will remain delinquent for at least y more days.

No one foresaw that scoring would replace individual analysis for consumer loans in high-income countries (Lewis, 1990). Further work will show the extent to which scoring can help cut the costs of microlending in low-income countries.

References

Boyes, William J.; Hoffman, Dennis L.; and Stuart A. Low. (1989) “An Econometric Analysis of the Bank Credit-Scoring Problem”, *Journal of Econometrics*, Vol. 40, pp. 3-14.

Eisenbeis, Robert A. (1981) “Credit-Scoring Applications”, pp. 167-198 in Edward I. Altman, Robert B. Avery, Robert A. Eisenbeis, and Joseph F. Sinkey, Jr. (eds) *Application of Classification Techniques in Business, Banking, and Finance*, Greenwich: JAI Press.

Greene, William H. (1998) “Sample selection in credit-scoring models”, *Japan and the World Economy*, Vol. 10, pp. 299-316.

_____. (1993) *Econometric Analysis: Second Edition*, New York: MacMillan.

_____. (1992) “A Statistical Model for Credit Scoring”, Stern School of Business Working Paper EC-92-29, New York University.

Hand, D.J. (1994) “Assessing Classification Rules”, *Journal of Applied Statistics*, Vol. 21, No. 3, pp. 3-16.

Hand, D.J.; and W.E. Henley. (1997) “Statistical Classification Methods in Consumer Credit Scoring: A Review”, *Journal of the Royal Statistical Association Series A*, Vol. 160, Part 3, pp. 523-541.

Jenkins, Stephen P. (1995) “Easy Estimation Methods for Discrete-Time Duration Models”, *Oxford Bulletin of Economics and Statistics*, Vol. 57, No. 1, pp. 129-138.

Kennedy, Peter. (1998) *A Guide to Econometrics, Fourth Edition*, Cambridge, MIT Press.

Lawrence, David B. (1992) *Handbook of Consumer Lending*, New Jersey: Prentice Hall.

Lewis, Edward M. (1990) *An Introduction to Credit Scoring*, San Rafael: Athena Press.

Mester, Loretta J. (1997) “What’s the Point of Credit Scoring?”, *Business Review*, Sept./Oct., pp. 3-16, Federal Reserve Bank of Philadelphia.

Navajas, Sergio; Schreiner, Mark; Meyer, Richard L.; Gonzalez-Vega, Claudio; and Jorge Rodriguez-Meza. (2000) "Microfinance and the Poorest of the Poor: Theory and Evidence From Bolivia", *World Development*, Vol. 28, No. 2.

Rhyne, Elisabeth; and Linda Rotblatt. (1994) "What Makes Them Tick? Exploring the Anatomy of Major Microenterprise Finance Organizations", Acción International Monograph Series No. 9, Washington, D.C.

Viganò, Laura. (1993) "A Credit-Scoring Model For Development Banks: An African Case Study", *Savings and Development*, Vol. 17, No. 4, pp. 441-482.

Wiginton, John C. (1980) "A Note on the Comparison of Logit and Discriminant Models of Consumer Credit Behavior", *Journal of Financial and Quantitative Analysis*, Vol. 15, No. 3, pp. 757-770.

TABLE 1
ESTIMATED EFFECTS OF EXPERIENCE OF BORROWER

Independent variable		Mean	Logit coefficients Estimate	s.e.	p-value	Change in prob. of exit Estimate	s.e.	p-value
Number of past loans	1	0.460	-0.812	0.147	0.01	-0.114	0.021	0.01
	2	0.247	-1.052	0.155	0.01	-0.148	0.022	0.01
	3	0.131	-1.322	0.165	0.01	-0.186	0.023	0.01
	4	0.070	-1.599	0.175	0.01	-0.225	0.025	0.01
	5	0.039	-1.512	0.187	0.01	-0.212	0.026	0.01
	6	0.022	-1.929	0.213	0.01	-0.271	0.030	0.01
	7	0.013	-1.861	0.243	0.01	-0.262	0.034	0.01
	8	0.008	-2.407	0.313	0.01	-0.338	0.044	0.01
	9	0.005	-2.222	0.334	0.01	-0.312	0.047	0.01
	10 or more	0.006	-2.152	0.321	0.01	-0.302	0.045	0.01
Months since first loan	0-6	0.636						
	7-19	0.233	-0.036	0.057	0.53	-0.005	0.008	0.53
	20-53	0.125	0.097	0.086	0.26	0.014	0.012	0.26
	54-147	0.007	0.423	0.196	0.03	0.059	0.028	0.03

TABLE 2
ESTIMATED EFFECTS OF PAST ARREARS

			Logit coefficients			Change in prob. of exit		
Independent variable		Mean	Estimate	s.e.	p-value	Estimate	s.e.	p-value
Longest spell in days	0	0.524						
in all past loans	1	0.168	-0.451	0.069	0.01	-0.063	0.010	0.01
	2	0.091	-0.323	0.085	0.01	-0.045	0.012	0.01
	3	0.060	-0.158	0.090	0.08	-0.022	0.013	0.08
	4	0.047	-0.097	0.097	0.32	-0.014	0.014	0.32
	5	0.027	0.031	0.109	0.78	0.004	0.015	0.78
	6	0.020	0.221	0.114	0.05	0.031	0.016	0.05
	7	0.028	0.481	0.102	0.01	0.068	0.014	0.01
	8-14	0.063	0.890	0.087	0.01	0.125	0.012	0.01
	15-21	0.025	1.588	0.102	0.01	0.223	0.014	0.01
	22-28	0.015	2.220	0.120	0.01	0.312	0.017	0.01
	29 or more	0.051	2.947	0.097	0.01	0.414	0.014	0.01
Number of spells	0	0.524						
in previous loan	1	0.091	0.176	0.076	0.02	0.025	0.011	0.02
	2	0.072	0.323	0.080	0.01	0.045	0.011	0.01
	3	0.059	0.517	0.083	0.01	0.073	0.012	0.01
	4	0.047	0.668	0.087	0.01	0.094	0.012	0.01
	5 or 6	0.072	0.868	0.079	0.01	0.122	0.011	0.01
	7 or 8	0.047	0.916	0.087	0.01	0.129	0.012	0.01
	9 or more	0.087	1.165	0.082	0.01	0.164	0.011	0.01

TABLE 3
ESTIMATED EFFECTS OF SEX, SECTOR, AMOUNT DISBURSED, AND GUARANTEE

Independent variable		Mean	Logit coefficients			Change in prob. of exit		
			Estimate	s.e.	p-value	Estimate	s.e.	p-value
Sex	Male	0.422						
	Female	0.578	0.079	0.034	0.02	0.011	0.005	0.02
Sector	Manufacturing	0.473						
	Trade	0.527	-0.146	0.045	0.01	-0.020	0.006	0.01
Changed sector		0.006	0.167	0.183	0.36	0.023	0.026	0.36
Amount disbursed	Level	676	-0.000130	0.000030	0.01	-0.000018	0.000004	0.01
	Increase	140	-0.000520	0.000078	0.01	-0.000073	0.000011	0.01
	Decrease	25	0.000085	0.000053	0.11	0.000012	0.000007	0.11
Guarantee	Other	0.029						
	Personal	0.475	-0.100	0.087	0.25	-0.014	0.012	0.25
	None	0.248	-0.031	0.090	0.73	-0.004	0.013	0.73
	Multiple	0.248	0.154	0.098	0.12	0.022	0.014	0.12
Changed guarantee		0.100	-0.005	0.058	0.93	-0.001	0.008	0.93

TABLE 4
ESTIMATED EFFECTS OF THE LOAN OFFICER

		Logit coefficients			Change in prob. of exit		
Independent variable	Mean	Estimate	s.e.	p-value	Estimate	s.e.	p-value
Other	0.054						
1	0.011	-0.981	0.176	0.01	-0.138	0.025	0.01
2	0.006	-0.939	0.248	0.01	-0.132	0.035	0.01
3	0.002	-0.912	0.340	0.01	-0.128	0.048	0.01
4	0.010	-0.908	0.209	0.01	-0.128	0.029	0.01
5	0.004	-0.866	0.251	0.01	-0.122	0.035	0.01
6	0.006	-0.764	0.225	0.01	-0.107	0.032	0.01
7	0.009	-0.736	0.221	0.01	-0.103	0.031	0.01
8	0.010	-0.689	0.201	0.01	-0.097	0.028	0.01
9	0.016	-0.682	0.175	0.01	-0.096	0.025	0.01
10	0.010	-0.669	0.194	0.01	-0.094	0.027	0.01
11	0.031	-0.527	0.201	0.01	-0.074	0.028	0.01
12	0.010	-0.519	0.173	0.01	-0.073	0.024	0.01
13	0.022	-0.506	0.183	0.01	-0.071	0.026	0.01
14	0.002	-0.481	0.331	0.15	-0.068	0.046	0.15
15	0.003	-0.480	0.291	0.10	-0.067	0.041	0.10
16	0.016	-0.458	0.514	0.37	-0.064	0.072	0.37
17	0.017	-0.432	0.514	0.40	-0.061	0.072	0.40
18	0.014	-0.420	0.222	0.06	-0.059	0.031	0.06
19	0.019	-0.345	0.121	0.01	-0.048	0.017	0.01
20	0.025	-0.341	0.134	0.01	-0.048	0.019	0.01
21	0.045	-0.307	0.128	0.02	-0.043	0.018	0.02
22	0.035	-0.294	0.107	0.01	-0.041	0.015	0.01
23	0.037	-0.274	0.129	0.03	-0.039	0.018	0.03
24	0.024	-0.239	0.123	0.05	-0.034	0.017	0.05
25	0.031	-0.179	0.128	0.16	-0.025	0.018	0.16
26	0.059	-0.159	0.113	0.16	-0.022	0.016	0.16
27	0.008	-0.132	0.168	0.43	-0.019	0.024	0.43
28	0.019	-0.125	0.144	0.39	-0.018	0.020	0.39
29	0.015	-0.119	0.153	0.44	-0.017	0.021	0.44
30	0.016	-0.099	0.186	0.60	-0.014	0.026	0.60
31	0.067	-0.089	0.110	0.42	-0.012	0.015	0.42
32	0.038	-0.086	0.122	0.48	-0.012	0.017	0.48
33	0.014	-0.085	0.153	0.58	-0.012	0.022	0.58
34	0.015	-0.083	0.155	0.59	-0.012	0.022	0.59
35	0.013	-0.083	0.143	0.56	-0.012	0.020	0.56
36	0.027	-0.052	0.137	0.71	-0.007	0.019	0.71
37	0.010	-0.034	0.229	0.88	-0.005	0.032	0.88
38	0.011	-0.030	0.131	0.82	-0.004	0.018	0.82
39	0.016	0.013	0.152	0.93	0.002	0.021	0.93
40	0.048	0.037	0.104	0.72	0.005	0.015	0.72
41	0.006	0.062	0.525	0.91	0.009	0.074	0.91
42	0.019	0.068	0.210	0.75	0.010	0.029	0.75
43	0.008	0.095	0.197	0.63	0.013	0.028	0.63
44	0.006	0.170	0.183	0.35	0.024	0.026	0.35
45	0.009	0.183	0.200	0.36	0.026	0.028	0.36
46	0.016	0.671	0.331	0.04	0.094	0.046	0.04
47	0.035	0.693	0.314	0.03	0.097	0.044	0.03
48	0.041	0.833	0.305	0.01	0.117	0.043	0.01
49	0.002	0.858	0.437	0.05	0.121	0.061	0.05
50	0.014	0.887	0.330	0.01	0.125	0.046	0.01
Changed loan officer	0.115	0.097	0.055	0.08	0.014	0.008	0.08

TABLE 5
ESTIMATED EFFECTS OF EXPERIENCE OF LOAN OFFICER AND BRANCH

			Logit coefficients			Change in prob. of exit		
Independent variable		Mean	Estimate	s.e.	p-value	Estimate	s.e.	p-value
Experience of loan officer	0-1	0.061						
in months	2-6	0.204	0.045	0.066	0.50	0.006	0.009	0.50
	7-19	0.322	0.155	0.070	0.03	0.022	0.010	0.03
	20-53	0.335	0.102	0.087	0.24	0.014	0.012	0.24
	54-147	0.078	-0.101	0.147	0.49	-0.014	0.021	0.49
Branch	Other	0.438						
	1	0.114	-1.646	0.304	0.01	-0.231	0.043	0.01
	2	0.040	-0.458	0.504	0.36	-0.064	0.071	0.36
	3	0.044	-0.307	0.178	0.09	-0.043	0.025	0.09
	4	0.078	-0.229	0.149	0.12	-0.032	0.021	0.12
	5	0.161	-0.212	0.104	0.04	-0.030	0.015	0.04
	6	0.072	-0.197	0.165	0.23	-0.028	0.023	0.23
	7	0.053	0.194	0.192	0.31	0.027	0.027	0.31
Changed branch		0.024	0.254	0.102	0.01	0.036	0.014	0.01

TABLE 6
ESTIMATED EFFECTS OF MONTH AND YEAR OF DISBURSEMENT

Independent variab		Mean	Logit coefficients			Change in prob. of exit		
			Estimate	s.e.	p-value	Estimate	s.e.	p-value
Year	1988-1991	0.083						
	1992	0.086	-0.185	0.077	0.02	-0.026	0.011	0.02
	1993	0.131	-0.556	0.097	0.01	-0.078	0.014	0.01
	1994	0.198	-0.782	0.115	0.01	-0.110	0.016	0.01
	1995	0.353	-0.482	0.123	0.01	-0.068	0.017	0.01
	1996	0.150	-0.119	0.141	0.4	-0.017	0.020	0.4
Month	January	0.056						
	February	0.064	-0.112	0.083	0.18	-0.016	0.012	0.18
	March	0.088	-0.054	0.078	0.49	-0.008	0.011	0.49
	April	0.091	-0.070	0.078	0.36	-0.010	0.011	0.36
	May	0.102	-0.152	0.077	0.05	-0.021	0.011	0.05
	June	0.096	-0.208	0.078	0.01	-0.029	0.011	0.01
	July	0.081	-0.190	0.082	0.02	-0.027	0.012	0.02
	August	0.081	0.030	0.081	0.71	0.004	0.011	0.71
	September	0.087	-0.094	0.080	0.24	-0.013	0.011	0.24
	October	0.086	0.048	0.080	0.55	0.007	0.011	0.55
	November	0.089	-0.017	0.080	0.83	-0.002	0.011	0.83
	December	0.079	0.045	0.082	0.58	0.006	0.011	0.58

TABLE 7
POWER TO PREDICT OUT-OF-SAMPLE

		Threshold										
		All-bad										All-good
Criteria	Formula	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
True positives	TP	0	1,771	4,231	5,499	6,062	6,338	6,514	6,644	6,721	6,783	6,794
True negatives	TN	3,761	3,367	2,635	2,127	1,799	1,534	1,287	1,034	764	284	0
False positives	FP	0	394	1,126	1,634	1,962	2,227	2,474	2,727	2,997	3,477	3,761
False negatives	FN	6,794	5,023	2,563	1,295	732	456	280	150	73	11	0
True positive rate	TP/(TP+FN)	0.00	0.26	0.62	0.81	0.89	0.93	0.96	0.98	0.99	1.00	1.00
True negative rate	TN/(TN+FP)	1.00	0.90	0.70	0.57	0.48	0.41	0.34	0.27	0.20	0.08	0.00
True total rate	(TP+TN)/N	0.36	0.49	0.65	0.72	0.74	0.75	0.74	0.73	0.71	0.67	0.64
Positive predictive value	TP/(TP+FP)	1.00	0.82	0.79	0.77	0.76	0.74	0.72	0.71	0.69	0.66	0.64
Negative predictive value	TN/(TN+FN)	0.36	0.40	0.51	0.62	0.71	0.77	0.82	0.87	0.91	0.96	1.00
Total predictive value	(TP+TN)/N	0.36	0.49	0.65	0.72	0.74	0.75	0.74	0.73	0.71	0.67	0.64

Note: N=10,555. With 6,794 known goods and 3,761 known bads, the known-good rate is 0.64, and the known-bad rate is 0.36.

FIGURE 1
POPULATION-WEIGHTED PROBABILITY DISTRIBUTION OF ESTIMATED RISK TO GO BAD FOR KNOWN GOODS

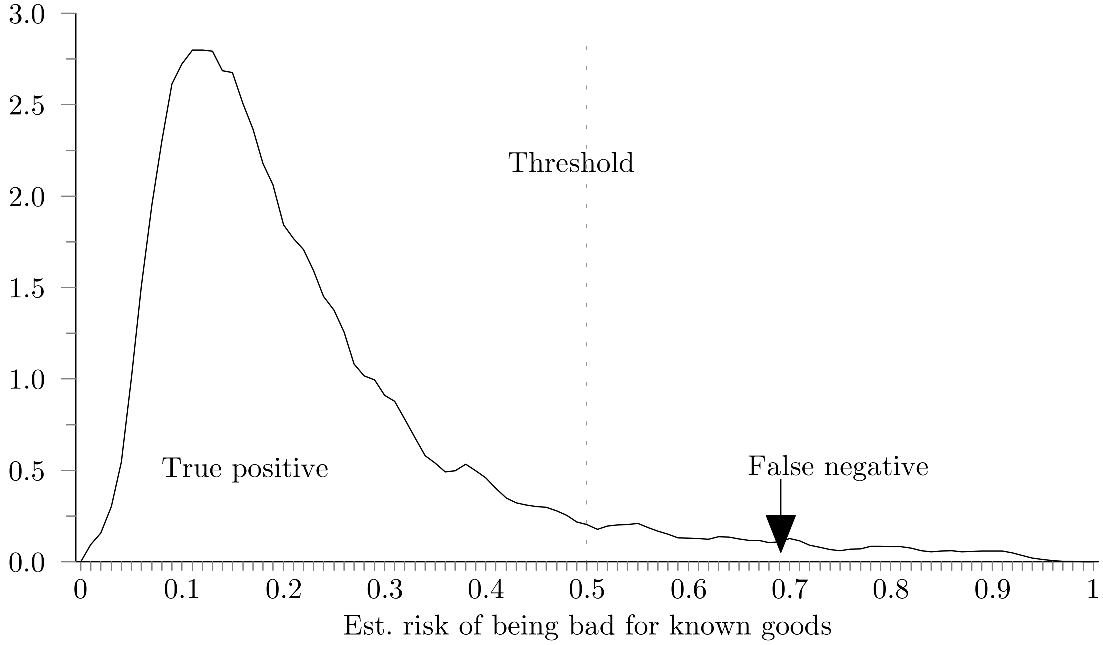

FIGURE 2
POPULATION-WEIGHTED PROBABILITY DISTRIBUTION OF ESTIMATED RISK TO GO BAD FOR KNOWN BADS

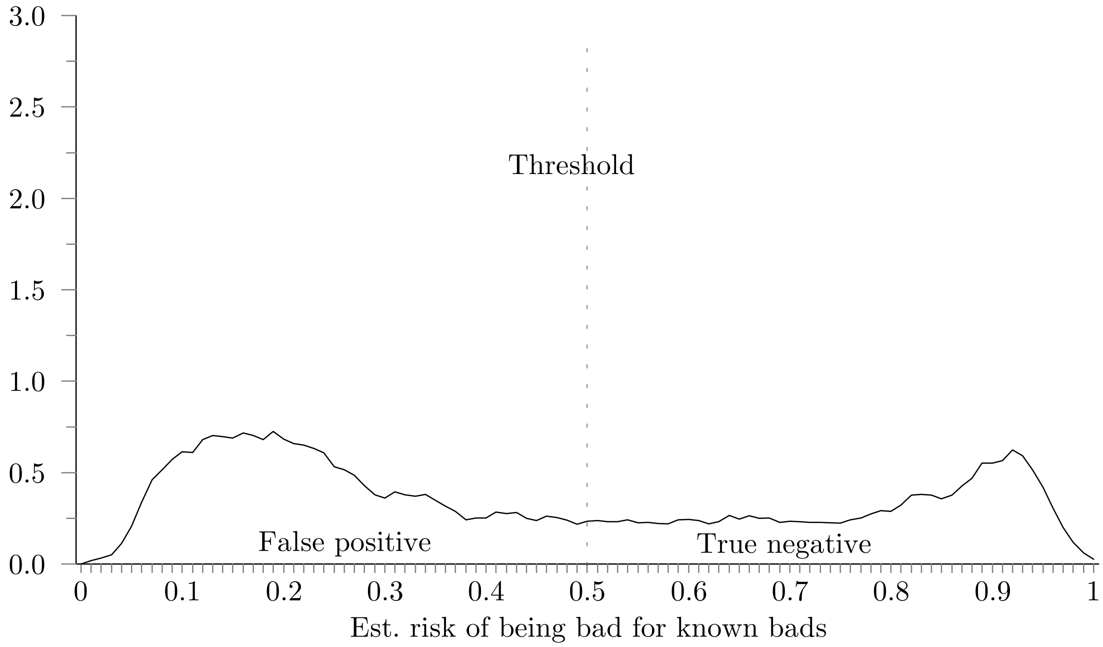

FIGURE 3
CUMULATIVE DISTRIBUTIONS OF ESTIMATED RISK TO GO BAD FOR KNOWN BADS AND TO STAY GOOD FOR KNOWN GOODS

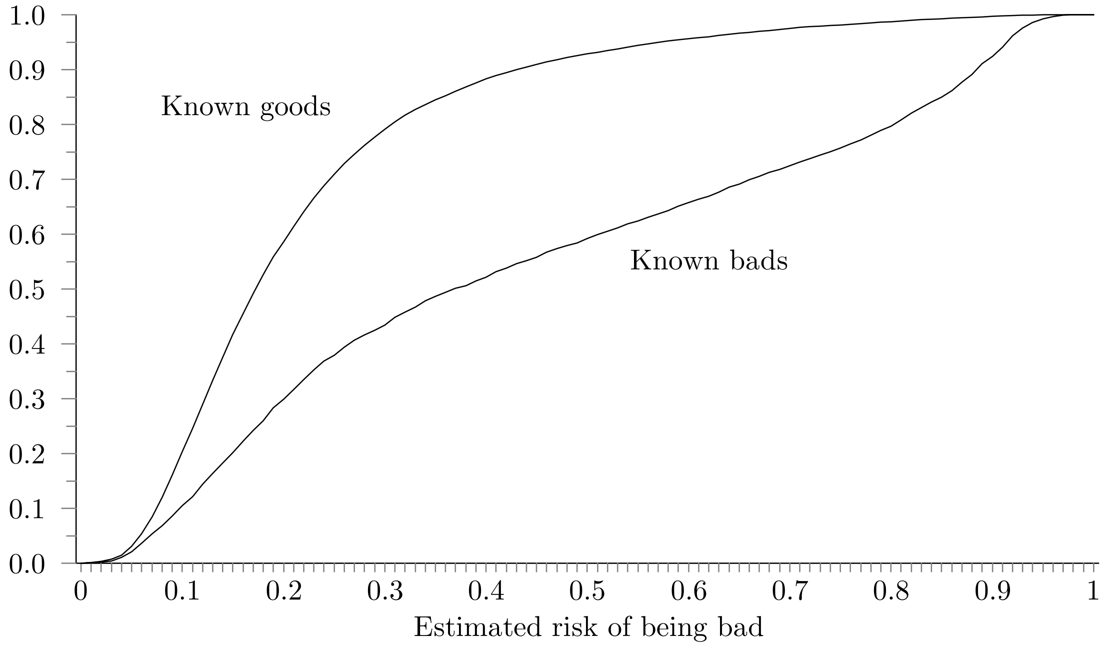

FIGURE 4
TRUE POSITIVE RATE, TRUE NEGATIVE RATE, AND TRUE TOTAL RATE FOR VARIOUS THRESHOLDS

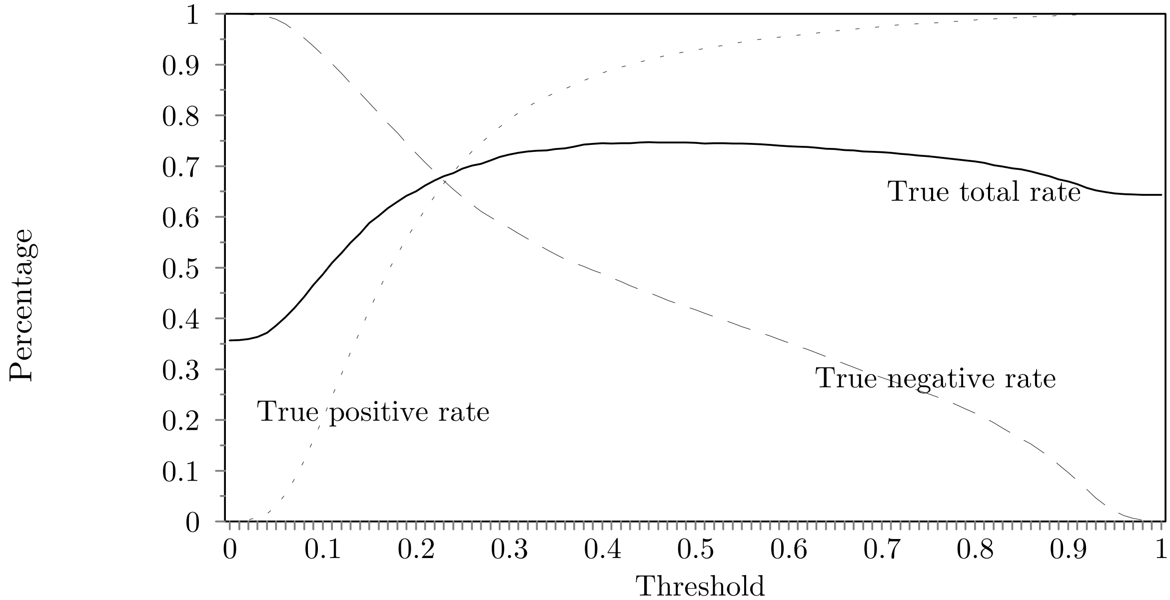

FIGURE 5
THE TRADE-OFF BETWEEN THE TRUE POSITIVE RATE AND THE TRUE NEGATIVE RATE

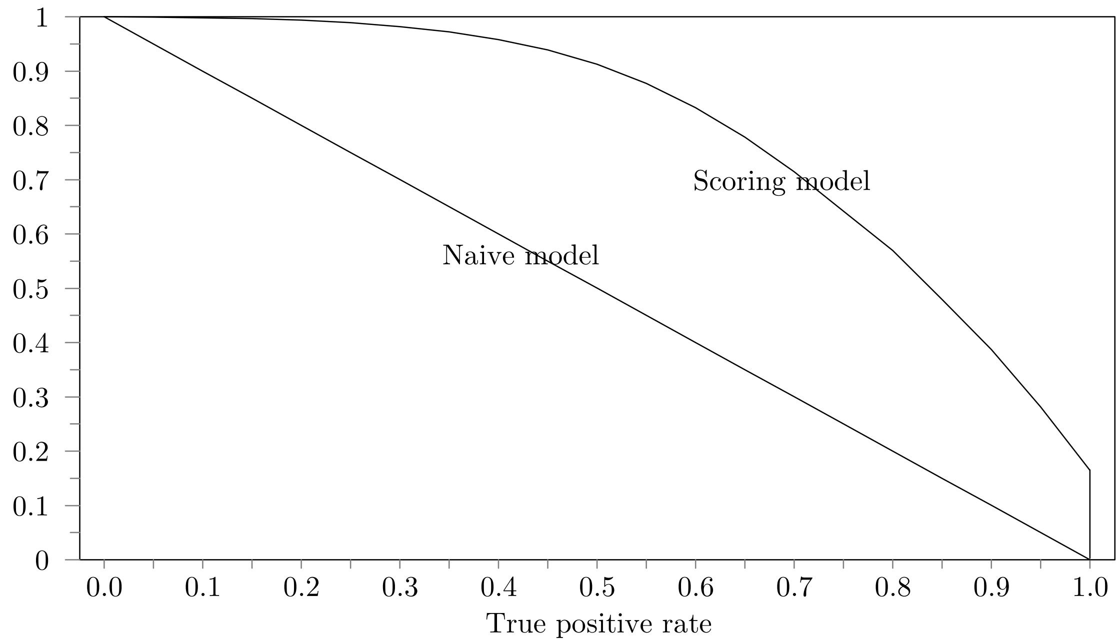

FIGURE 6
POSITIVE PREDICTIVE VALUE,
NEGATIVE PREDICTIVE VALUE,
AND TOTAL PREDICTIVE VALUE
FOR VARIOUS THRESHOLDS