ASSESSING THE EFFICACY OF A SOUTH AFRICAN MICROLENDER'S LOAN SCREENING MECHANISM

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Bivariate probit analysis was used to assess the efficacy of a South African microlender's loan screening process. This micro-lender grants short-term cash loans to individuals who are employed and earning a fixed salary. Loan applicants with more stable incomes, who are contactable via telephone or post, who are employed in less risky business sectors, who have more disposable income relative to debt, and who have had a good credit history with other lenders, are more likely to be accepted. None of the factors with a significant effect on the loan screening decision could explain subsequent loan default by accepted applicants. The micro-lender may have screened out very risky clients and accepted a riskier, profitable pool of loan applicants with risk being controlled through effective monitoring. This is important where tangible collateral is unavailable and where the risk must be acceptable to commercial lenders wanting to link up with profitable micro-lenders.

1. INTRODUCTION

Lenders seek cost-effective financial technologies that can assimilate information on loan applicants to correctly assess credit worthiness, reduce the incidence of incorrect credit rationing, lower borrower and lender transaction costs, and manage loan default to ensure financial viability (Hoff & Stiglitz, 1990). The micro-lending industry in South Africa serves mainly lower-income clientele employed in the formal sector of the economy, earning a fixed monthly salary, having limited or no collateral and where information is difficult or costly to come by (Du Plessis, 1997). Cost-effective loan applicant screening and loan contract enforcement are thus important to reduce adverse selection (lender incorrectly granting a loan to a risky client) and moral hazard (client takes on a riskier project than agreed to in the loan contract) (Barry *et al*., 1995). However, in their studies Boyes *et al* (1989) and Jacobson and Roszbach (1998), show that the scoring process of lenders may not only be designed to minimise loan default risk but also to maximise profit. Their work is adapted in this study to assess the efficacy (competence) of the loan screening process used by a South African micro-lender (who for confidentiality purposes cannot be named). An effective loan screening mechanism is important given that tangible collateral such as bank cards are

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no longer permitted and that government will stop deducting loan payments from employee salaries.

Effective screening and contract enforcement can also improve the potential for micro-lenders to enter into joint ventures with commercial banks, who are looking to expand into the micro-lending market, but lack the appropriate financial technologies to do so (Robertson, 2000). Several South African studies (see Kuhn & Darroch, 1999 for a summary) have estimated factors influencing loan default but have not analyzed the efficacy of the loan screening process which requires using data on *both* accepted and rejected loan applicants. This study will help to close this gap in the South African micro-finance literature. Section two outlines the economic theory of loan screening and specifies an appropriate model for assessing the efficacy of loan screening. Sections three and four describe the study data and present results of the empirical model. A concluding section highlights credit management and policy implications of the study.

2. THE LOAN SCREENING MODEL

Numerous studies have linked loan repayment performance to borrower personal and employment characteristics, previous loan histories or micro-lender traits (see, for example Boyes *et al*, 1989; Jacobson & Roszbach, 1998; Kuhn & Darroch, 1999 and Schreiner, 1999). Lenders can obtain a competitive advantage by developing screening models that can cost-effectively identify high and low-risk borrowers. This also has important advantages for the potential borrowers, as it may reduce the incidence of incorrectly rationing low-risk low-income loan applicants (Chaves & Gonzalez-Vega, 1996). To test the efficacy of the loan screening decision, information on both accepted and rejected applicants, and the loan repayment performance of accepted loan applicants, is needed. Client characteristics used in making the loan granting decision can then be compared to characteristics that influence loan default to determine whether the loan screening process is effective in correctly identifying high- and low-risk borrowers (Hunte, 1993). Lenders operating in a competitive environment may, however, not only want to minimise loan default risk but also may want to try and maximise profit. Boyes *et al* (1989) showed that profit-maximising commercial lenders may compromise, and accept relatively riskier clients that are potentially more profitable.

The econometric model used in this study to assess the efficacy of loan screening consists of two simultaneous equations - one for the binary decision to grant a loan or not y_{1i}, and the other for the binary outcome, default or repayment, y_{2i}. as follows:

$$\mathbf{y}_{1i}^{*} = \beta_1 \mathbf{X}_{1i} + \varepsilon_{1i} \qquad \mathbf{2.1}$$

$$\mathbf{y}_{2i}^{*} = \beta_2 \mathbf{X}_{2i} + \varepsilon_{2i} \qquad \mathbf{2.2}$$

where * indicates an unobserved latent variable, β_1 and β_2 are vectors of model coefficients to be estimated, and X_{ij} are the 1 x Kj vectors of explanatory variables (e.g. client characteristics like income and credit history) when the loan application is made. The binary choice variable y_{1i} equals 1 if the loan application was granted, and 0 if the application was rejected. The binary choice variable y_{2i} equals 1 if the approved loan was repaid more than 50 days in arrears or handed over for collection, and 0 if the loan was repaid. Given that sample borrowers had, on average more than two loans during the January 1998-June 1999 loan monitoring study period, repayment performance on the second loan was analyzed to avoid a substantial time lapse in which the characteristics of the accepted loan applicants may change. Note that y_{2i} is observed *if and only if* $y_{1i} = 1$. These equations can be estimated independently to assess the efficacy of the loan screening process. The truncation resulting from the selection rule can, however, lead to biased parameter estimates in equation (2.2) if the loan granting decision is not deterministically governed by the borrower attributes such that the error terms of the two equations are correlated (Greene, 1990). Meng and Schmidt (1985) show that there are efficiency gains in jointly estimating the two equations – which accounts for potential correlation between the equations and, thereby, for potential sample selection bias.

Given that the dependant variables are binary, a "censored" bivariate probit model with partial observability is specified and β_1 and β_2 vectors of coefficients are estimated by the method of maximum likelihood (Meng & Schmidt, 1985 give the appropriate log likelihood function). The level of significance and the signs of parameters estimated in equation (2.1) can be compared to the level of significance and signs of the parameter estimates in equation (2.2). A positive (negative) and significant coefficient in equation (2.1) and a negative (positive) and significant coefficient for the same variable in equation (2.2), indicates that the lender considered the variable in a manner that is consistent with a strategy to minimise loan default. Significant and positive signs for coefficients of the same variables in both equations implies that the loan granting decision runs counter to a default minimisation lending policy. This may be consistent with a lending policy designed to seek out riskier clients as these may still be profitable.

The study micro-lender assessed loan applicants according to their stability, contactability, affordability and credit history. This led to high multicollinearity between potential explanatory variables, as several measures were used for each characteristic. Proxies for the Xj explanatory variables in equation (2.1) and (2.2) were, therefore, specified to try and best represent these client attributes, while at the same time trying to reduce the incidence of multicollinearity. Client stability is represented by marital status (MARDUM) and unemployment category (EMPCAT); Contactability by home ownership and access to a post box (TELPOST); Loan affordability by monthly rental and debt commitments relative to monthly income (COMMIT), and credit history by loan arrears status with other lenders (ARRDUM) as follows:

MARDUM = 1 if the applicant was single or divorced, and 0 if the applicant was married or widowed,

EMPCAT = 1 if the applicant is a low-income employee in the entertainment/hospitality industry, the security guard/retailers/financial services, professional services (lawyers, accountants), army/police, or government departments dealing with labour, land affairs, transport, welfare, correctional services, water affairs and home affairs) and 0 if the applicant is a low-income employee in non-food manufacturing, construction, textiles and foods, health, and education sectors,

TELPOST = 1 if the individual had a home telephone, and 0 otherwise,

COMMIT = 1 if monthly rent plus retail debt commitments exceed 16% of the applicant's monthly net income, and 0 if they are less than 16% of the monthly net income, and

ARRDUM = 1 if the applicant had loans with other lenders in the 18 months prior to the application that were 120 days or more in arrears, or had previous bad debt write-offs, and 0 if the loan applicants had no adverse loan details

Marital status and employment category, are used by the micro-lender's loan officers as indicators of the potential stability of their client's future income status. Given that a loan contract is based on a promise to repay in the future, loan applicants must be able to give lenders an indication of the stability of potential future incomes (Barry *et al*, 1995). Jacobson and Roszbach (1998) and

Boyes *et al* (1989) show that borrowers who were married, and who owned homes had greater probabilities of obtaining loans, and were better credit risks. This suggests that MARDUM should be negatively related to loan approval and positively to loan default. The sector in which loan applicants are employed is also likely to indicate the relative stability of future income streams, as some sectors are likely to provide more stable incomes than others do. Hunte (1993), Kuhn and Darroch (1999), and Schreiner (1999) all include variables on employment or business sector to account for this factor. The study micro-lender's loan officers felt that low-income earners in the hospitality, security, financial services, professional services, police, and some government sectors were particularly prone to retrenchments, and were thus relatively greater credit risks. This suggests that EMPACT could be negatively related to the loan approval and positively related to loan default.

Lenders can increase the likelihood of loan repayments by regularly monitoring clients and/or increasing the borrowers' stake in the investment (Hayami and Otsuka, 1993). The technologies used to monitor clients and enforce contracts are likely to depend on the lender's resources, the legal and regulatory framework and the target clientele. The study micro-lender's clients typically have little or no tangible collateral and so loan contracts are enforced through intensive monitoring via telephone (visits to clients by the loan officers are considered too costly). Clients with a home telephone are regarded as being contactable. TELPOST should hence be positively related to the loan granting decision and negatively related to loan default.

The COMMIT variable shows the borrower's potential ability to meet new debt commitments. Applicants with more existing commitments against net monthly income have relatively less disposable income available to finance new debt. A negative relationship between COMMIT and the loan granting decision is expected, while COMMIT should be positively related to loan default

Reputational capital is an important collateral substitute used by micro-lenders to enforce loan contracts, and depends on the applicant's repayment record. Clients with good repayment records may be regarded as better credit risks and their reputation thus has higher value (Hayami & Otsuka, 1993). Previous loan history in South Africa can be assessed via a network of credit bureaus that collect loan repayment and loan default information from various consumer credit forums. ARRDUM is thus hypothesised to negatively influence the loan granting decision and be positively related to loan default.

The sign of the correlation coefficient between the loan granting equation (2.1) and the loan default equation (2.2) shows the extent to which non-systematic tendencies to grant loans are correlated with non-systematic tendencies in default risk. A positive correlation coefficient implies that the subjective elements in the study micro-lender's loan policy that increase a loan applicants odds of being granted a loan, are positively related to loan default (Boyes *et al*, 1989). This is consistent with a loan policy that attempts to seek out relatively riskier clients that potentially offer greater expected returns. Section 3 reviews the data used to estimate these equations, while Section 4 discusses model results.

3. DATA

Data for 800 first-time loan applicants during 1 January 1998-30 September 1998 were gathered from the micro-lender's Ladysmith, Pietermaritzburg and Pretoria branches. A total of 728 cases could be analyzed, as 65 applications were subsequently cancelled. Of the 728 sample applicants, 309 were granted credit, while 419 were rejected. Loan repayment performance of the accepted loans was then tracked through to 30 June 1999. Of the 309 accepted loan applicants, 40 (12%) had repaid their loans more than 50 days in arrears or were handed over. The average loan size granted to sample applicants was R950. The micro-lender did not use client bankcards as collateral and did not ask employers to deduct loan installments from monthly salaries. The screening and monitoring technologies used by the study lender were thus crucial in ensuring successful loan recovery. Sixty percent of the loan applicants were male. Thirty-seven percent of the applicants owned the residence in which they lived, and 15% had a housing bond with a commercial bank or through their employers. Sixty percent of the sample applicants were employed in the private sector and 40% in the government sector. The average monthly basic and net salary of those employed in the private sector was R1991 and R1598, compared to R3172 and R1881 in the government sector. Most of the sample applicants (84%) had previous credit experience.

4. RESULTS

The bivariate probit model coefficient estimates are presented in Table 1. A residual deviance of –450.64 with 640 degrees of freedom shows no significant lack of fit. The signs of the parameters for the loan approval/rejection decision meet *a priori* expectations. Loan applicants with less stable, income, that could be contacted less readily, who worked in more risky sectors, with proportionally more monthly commitments against net income, and who had delinquent accounts with other lenders were rejected. Characteristics used in the loan screening decision tend to have less influence on loan repayment. Only employment category (EMPCAT) has a statistically significant coefficient at the 10% level showing that sample borrowers employed in these sectors have a lower probability of default which is contrary to what the study lender expected in the screening decision. Insignificant coefficients in the loan default equation may not necessarily show that the study lender's screening mechanism is ineffective, but that very high-risk borrowers have been successfully eliminated at the screening stage with a risky, but more profitable, client pool being accepted. This supports the significant, positive correlation coefficient (ρ) between the two equations. Non-payment of loans may be as a result of exogenous shocks that are unpredictable at the time of loan granting or moral hazard where the borrower may take on more debt during the loan contract.

Table 1 Results of Bivariate Probit Model

	Equation (2.1): P (loan approval)	**Equation (2.2): P (loan default)**
Constant	0.19758 (1.437)	-1.69107 (-7.524)
MARDUM	-0.59967** (-1.933)	-0.59967 (-0.314)
TELPOST	0.54573*** (4.329)	0.340655 (1.524)
EMPCAT	-0.23409** (-2.056)	-0.37500* (-1.803)
COMMIT	-0.24684** (-2.182)	0.18179 (0.9341)
ARRDUM	-1.2619*** (-11.008)	0.22009 (0.9472)
ρ (1,2)	0.91608	0.91608** (2.012)

***, **, * *Indicate significance at the 1%, 5% and 10% levels respectively.*

The impact of this additional debt may only become evident when the borrower defaults. Reputational capital, while being very important in the initial screening stages, has no influence on borrower repayment indicating that high risk borrowers with poor reputational capital may be effectively screened out at loan application. The non-significance of contactability in predicting loan repayment performance is expected, as all successful loan applicants must be contactable. This highlights the importance of the monitoring mechanism in controlling loan default. Loan officers indicated that, while a riskier pool of clients may be accepted, the clients are closely monitored with any non-payment on the due date being immediately followed-up by telephonic contact with the borrower. Thus the lender relies heavily on the monitoring technology to control arrears while screening out very risky clients at loan application.

5. CONCLUSIONS

Accurate screening of loan applicants is critical in the credit granting process and depends on the screening technology used by the lender and information available. Although default minimisation is crucial to ensuring financial success of lenders, research has shown that lenders may accept riskier clients in trying to maximise profits. However, the riskier pool of borrowers must be managed through effective loan contract enforcement. Study results show that few sample applicant characteristics are important in explaining loan default. This may not necessarily imply a poor screening mechanism but may show that the study lender is able to effectively screen out very high-risk loan applicants. Moral hazard in the relatively riskier, but more profitable borrower pool, is managed through a strict monitoring technology where frequent lender-borrower contact is effected by telephonic means. Cost effective screening and monitoring technologies will gain increasing importance, as microlenders are no longer able to retain bankcards as collateral. This is particularly so for microlenders seeking partnerships with commercial lenders such as banks. Infrastructural development (communication networks) in rural areas may facilitate the monitoring process. In addition, microlenders should be encouraged to develop reputational capital by supporting credit bureaus with accurate credit records of clients.

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